Logothetis, Ioannis (2012) Hedge Funds & The Alpha Paradigm. [Dissertation (University of Nottingham only)] (Unpublished)

University of Nottingham

Hedge Funds & The Alpha Paradigm

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Master of Science in Finance & Investment

Hedge Funds & The Alpha Paradigm

by

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September 2012

A Dissertation presented in part consideration for the degree:
'Master of Science in Finance and Investment'

Abstract

Numerous heavily quantitative strategies, macroeconomic and esoteric investment techniques involving currencies, fixed income products, commodities and equities have proven to be very profitable over the last two decades as math whizzes of Wall Street implemented mathematical and quantum physics models to outperform financial markets in search of Alpha. The development of mathematical algorithms, exotic trading techniques, lightening fast computerized machines and platforms and the effective in-depth skilful macroeconomic analysis from numerous hedge fund managers have resulted in trillions of profits or even losses which have in turn affected the global financial system significantly. This thesis will examine the features of the hedge fund industry focusing on the analysis and the background of the 'Alpha' paradigm, the various profitable strategies on record, their performance over the years, the recent developments in the field, their influence and their effects on the global economy and the financial system with the infamous events of 2007-2008 serving as a backdrop. By assessing historically the hedge fund performance it could be demonstrated that hedge funds produce superior risk-adjusted returns over time comparing with traditional assets, and they carried fewer risks when the volatilities are compared. Our findings also support that hedge funds possess the ability create alpha consistently and systematically with limited volatility and by outperforming traditional asset classes, while there is a limited interaction between hedge fund returns and systematic market factors.

Contents

List of Figures 5
List of Tables 6
Acknowledgements 7
1 Prelude 8
1.1 Background and Context 9
1.2 Scope and Objectives 10
1.3 Overview of Dissertation 11
2 State-of-The-Art 12
2.1 History & Characteristics 12
2.2 Generating and Chasing Alpha 14
2.2.1 What is Alpha and Beta? 14
2.2.2 Driver of Alpha returns 16
2.3 Hedge funds Performance 18
2.3.1 Performance measurement and modelling of returns. 18
2.3.2 Drivers of Returns and Factor Selection 19
2.3.3 Survivorship Bias 21
2.3.4 Performance Persistence 22
2.4 Strategies 24
2.5 Summary of the academic research and key trends 29
2.6 Market Impact to the global financial markets 30
2.6.1 Historical examples 31
2.6.2 What happened to the 'Quants' in 2007 32
2.6.3 Concluding remarks 34
3 A Quantitative Approach in the corridors of the Industry 35
3.1 Databases 35
3.1.1 Hedge Fund Dataset 35
3.2 Methodology 38
4 Empirical results 43
4.1.1 Do Hedge funds produce superior risk-adjusted returns in comparison to traditional assets? 43
4.1.2 Do hedge funds strategies achieve statistical significant different mean monthly returns through time? 47
5 Conclusion 53
6 References 56
7 Appendices 64

7.1 Appendix 1 .... **64**
7.2 Appendix 2 .... **65**
7.3 Appendix 3 .... **66**
7.4 Appendix 4 .... **67**
7.5 Appendix 5 .... **68**
7.6 Appendix 6 .... **69**
7.7 Appendix 7 .... **71**
7.8 Appendix 8 .... **73**

List of Figures

1.Hedge Funds Versus Traditional Asset Classes……………………………………….45

2.Market Beta Vs Hedge Funds Vs MSCI………………………………………………51

3.Industry Trends: Estimated number of hedge funds…………………………………...63

4.Industry Trends: Estimated growth of Assets/Net Asset Flow…………………………64

5.2000-Bursting of the Internet Bubble…………………………………………………66

List of Tables

1. **Four global categories of hedge fund academic studies.…………………………………..28**
2. **Categorizations of hedge fund strategies and differences from academics and practitioners.………………………………………………………………………………29**
3. **CS/Tremont hedge-fund index returns for the month of August 2007: Index / Sub Strategies.……………………………………………………………………………….33**
4. **Descriptive statistics of the monthly index returns.……………………………………….36**
5. **Analytical Performance over 1998 - 2011 period.…………………………………………42**
6. **Analytical Performance over 1998 - Mid 2007 period.……………………………………43**
7. **Analytical Performance over Mid of 2007- Mid of 2012 period.…………………………44**
8. **Factors which have been indentified to drive hedge fund returns.………………………65**
9. **Display of Paired T-Tests Results.……….…………………………………………….....68**
10. **Display of Pair-wise Correlation Coefficients..……………………………………………70**
11. **Detailed Multi-Factor Model Results...…………………………………………………..72**

Acknowledgements

'If I have seen further, it is by standing on the shoulders of Giants'.

Taking a leaf from the great Isaac Newton, I would like to thank my mentor, Wasim Rehman, Managing Partner at the FWE Group, for his consistent guidance, nurturing, inspiration and encouragement. My greatest appreciation.

I would also like to thank my supervisor, Dr. David Newton who provided me with support and advice whenever I needed and for his flexibility for the structure of this thesis.

Finally, I would like to thank my close friend Yaw Kyei for acting as a second eye and a bouncing board of the available literature on my chosen subject matter.

1 Prelude

The world thinks that hedge funds are a magic road to riches for the manager and the investor. That's an illusion and a dangerous one (Barton Biggs, 2006).

A layman walking on the streets might not know exactly what a hedge fund is but may be aware of the recent furore surrounding these alternative investment vehicles – especially after the headlines generated by the Bernard L Madoff $50billion Ponzi scheme. An article in Bloomberg Markets Magazine in 2011 notes that: 'Brownstein's Mortgage Metaphysics Drives Gains in Top Hedge Fund: the $1.2 billion fund under the top ranked manager skyrocketed by 135% with mortgage bonds and complex credit derivatives - 135% in a depressed global economy?

To the layman – a hedge fund is a pooled investment fund, usually taking the shape of a private partnership which seeks to maximize absolute returns by using a broad range of strategies, including illiquid and unconventional investments. After the near bankruptcy of Long-Term Capital Management (LTCM) in 1998 along with speculative moves such as the ones undertaken by George Soros in 1992 on the British pound or the famous Credit Default Swap (CDS) trade by John Paulson which made him and his clients more than $20 billion, the attention of regulators have been drawn to the potential threat which the hedge fund industry pose to the financial stability of global markets.

The last two decades have witnessed a growing interest in hedge funds from investors, academics along with regulators. Investors and academics are intrigued by the unconventional performance characteristics associated with hedge funds while regulators are concerned with the market impact of their reported speculative activities during major market events. A hedge fund can be defined as a private investment fund which may be involved in investing in a diverse range of assets and may employ a variety of investment strategies to maintain a hedged portfolio intended to protect the fund's investors from downturns in the market while maximizing returns on market upswings as well as market downturns (W. Fung and Hsieh, 2004). Owing to the fact that hedge funds are typically organized as private investment vehicles for wealthy individuals and institutional investors, they do not disclose their activities publicly. Hence there is little information to assess the risk and the performance of the strategies which they employ. The lack of performance reporting standards and the relatively short history of hedge fund returns further make it hard to assess their long-term performance behaviour. It is simply not easy for investors to determine the role of hedge funds in their portfolio and the appropriate amount of exposure to hedge fund strategies (W. Fung and Hsieh, 2007).

Historically, in good as well as in bad times, certain hedge funds have been identified to predict market failures by outperforming and generating enormous profits using risky bets and strategies. Some very good examples are the well-known hedge funds of successful investors such as Dr. Michael Burry, Steve Eisman and John Paulson who had foreseen the madness of the subprime market peak and its associated securitization business. To illustrate, in advance of the upcoming event, they bet against the housing and subprime market by heavily purchasing uncovered CDS contracts for every single Collateralised Debt Obligation (CDOs) and Asset Backed Security (ABS) they could possible find. Back in 2005 and 2006, these cheap positions seemed incoherently speculative and to many investors who had money with these particular hedge funds. However, in 2007-2008, they benefited from enormous returns of more than 300% on their capital when the housing and the subprime market collapsed (M. Lewis, 2009).

1.1 Background and Context

Numerous heavily quantitative strategies, macroeconomic and esoteric investment techniques involving currencies, fixed income products, commodities and equities have proven to be very profitable over the last two decades as math whizzes of Wall Street implemented mathematical and quantum physics models to outperform financial markets in search of Alpha. The development of mathematical algorithms, exotic trading techniques, lightening fast computerized machines and platforms and the effective in-depth skilful macroeconomic analysis from some hedge fund managers have resulted in trillions of profits or even losses which have in turn affected the global financial system significantly. Hedge fund powerhouses such as Citadel Investment Group, AQR, PDT and Renaissance Technologies under massive leverage levels are undertaking ingenious investment strategies driven by the fields of cryptanalysis, computerized speech recognition, astrophysics, statistics and advanced mathematics to find profitable patterns and new investment opportunities. There are some "scientists" behind these scientific developments within the financial industry, usually referred to as *'Quants'*. They are highly paid specialists with degrees in the quantitative sciences and are employed by financial houses to create models which will be able to predict future price movements of securities, commodities, currencies and other financial products. Quants have strong skills in mathematics, engineering or computer science and they transfer these skills to the financial markets.

This thesis will examine the features of the hedge fund industry focusing on the analysis and the background of the 'Alpha' paradigm, the various profitable strategies on record, their performance over the years, recent developments in the field, their influence and their effects on the global economy and the financial system with the infamous events of 2007-2008 serving as a backdrop.

1.2 Scope and Objectives

The outlined questions below will be particularly addressed and analysed:

* What is alpha and beta within the hedge fund industry?

* What investment strategies are employed by these investment vehicles?

* How do Hedge funds and their strategies affect global capital markets and the real economy?

* Do hedge funds produce risk-superior adjusted returns relative to traditional asset classes?

* Do hedge funds strategies achieve statistical significant different mean monthly returns through time?

* What is the driver of hedge fund returns: alpha, beta (systematic market exposure) or other factors? How can alpha and beta interact? Is the market beta a constant or is it variable and how does it evolve over time?

An effort will be made to use some econometrics models to compare the returns of the strategies over time, determine whether hedge funds create uncorrelated returns and what leads them to incur abnormal returns over time. Finally, there is a personal objective to observe if the Hedge Fund industry really affects the financial system and the global economy negatively or positively. The reason behind this research is the interest in this particular industry/field and the recent aforementioned developments which some claim to have changed the global financial system significantly.

It is my belief that there is a lack of information in existing published academic papers with regards to the nature of some strategies and the effects of hedge funds on the financial markets. Apart from significant amount of research papers for the theoretical component obtained from Google Scholar and Nottingham University's online library, the thesis will use a significant amount of data obtained from the Bloomberg Terminal, Reuters 3000xtra and Hedge Fund research databases. These data will be modelled using the econometric package Stata.

As a prelude to the recent financial crisis, the world had seen the biggest and most profitable trades ever made by investment houses on Wall Street and The City. However, concurrently, the biggest financial turmoil on record with respect to the Great Depression has been brought on as a consequence of these self-effacing investment vehicles. In spite of the slump created by the recent crisis in the industry, it appears to have recovered with more investors seeking to invest in these funds in a bid to increase their wealth. In addition, the trend suggests more young bright minds are seeking their fortunes and career progression by joining these investment vehicles thus one can envisage more big trades and the development of more ingenious quantitative strategies in the coming future.

1.3 Overview of Dissertation

This extensive financial research on hedge funds and ‘alpha’ returns is separated into two main parts. The first part starts with a considerable amount of literature and theoretical analysis covering different aspects of the industry such as its history, the alpha paradigm, performance measurement and the key drivers of hedge fund returns, their strategies and the effects on the global financial marketplace. The second part covers a quantitative analysis which consists of performance measurement over a 14-year period along with applied statistical tests and a multi-factor regression analysis seeking to identify the drivers of hedge fund returns. Finally, this thesis draws a wide conclusion of the different aspects which were covered within the research and some personal thoughts and insights.

2 State-of-The-Art

2.1 History & Characteristics

"During the French Revolution such speculators were known as agitateurs, and they were beheaded’. Michel Sapin

In the late 1940s, the financial industry saw the birth of the first hedge fund, in an article written by the fund’s founder, A. W. Jones, he proposed the utilization of short-selling to hedge stock positions. Incentive fees and leverage were introduced by him as part of hedge fund management and strategies. However, the economist and investor Benjamin Graham is widely known as the father of value investing. He is also deemed as the father of the hedge-fund industry by some. “Ben Graham managed a hedge fund in the mid-1920s” Buffett wrote in a letter to the Museum of American Finance. “It involved a partnership structure, a percentage-of-profits compensation arrangement for Ben as a general partner, a number of limited partners and a variety of long and short positions”(Bloomberg, 2012).

In the late 1960s, nearly 140 funds were launched, many of which used substantial leverage. Many of them experienced high losses and bankruptcies during the bear markets of 1969–1970 and 1973–1974. The following years were relatively calm until the 1987–1993 period, which saw astonishing returns for some funds and a massive expansion in the number of funds created (S.C. Anderson et al, 2010). In the early 1990s, there were approximately 500 hedge funds worldwide with assets of $38 billion. The flood of cheap money in capital markets, the high risk appetite from investors and investment banks, endless financial innovation and the global growth in the financial industry led to in 2011, an industry with more than 9,500 funds (see appendix 1) and assets in excess of $2 trillion (see appendix 2).

“The term 'hedge fund' is undefined, including in federal securities law. Indeed, there is no commonly accepted universal meaning. As hedge funds have gained stature and prominence, though, 'hedge fund' has developed into a catch-all classification for many unregistered privately managed pools of capital. These pools of capital may or may not utilize the sophisticated hedging and arbitrage strategies that traditional hedge funds employ, and many appear to engage in relatively simple equity strategies. Basically, many 'hedge funds' are not actually hedged, and the term has become a misnomer in many cases” (William H. Donaldson, 2003)

S.C. Anderson et al (2010) defines hedge funds as private limited partnerships that accept investor's money and invest it in a pool of different financial securities. They employ trading strategies using financial derivatives, financial leverage, shorting positions to exploit market inefficiencies, combining traditional and non-traditional asset classes. The managers generally charge an administrative fee of 1% of the year's average net asset value. For the services provided, the hedge fund manager normally receives an incentive fee of 20% of the net profits of the partnership and they are subject to the antifraud provisions of federal securities laws.

As the investment management industry developed heavily over the last two decades, funds have been separated into absolute-return funds and directional funds. An absolute-return or pure alpha fund aims to generate a steady return irrespective of the market direction. The fund manager tries to remove all market risk in order to create an investment portfolio which doesn't vary with market performance. Directional funds aim for high returns without fully hedging their position and by maintaining some exposure to the market.

Certain hedge funds engage in very risky and complex strategies employing knowledge and tools from many different scientific fields by chasing abnormal returns thus some of them are prone to failures. An accurate example is the collapse of LTCM whose risky leveraged strategies made it particularly vulnerable to the freak storm which developed in the financial markets after the collapse of the Russian economy/stock market (Edwards, 1999). The implication of the potential failure of a systemically important hedge fund such as LTCM could be highlighted by the fact that the Federal Reserve of America arranged its bailout because capital markets were perceived to be particularly fragile after the Russian meltdown and the then Governor of the Fed, Alan Greenspan and his team wanted to halt possible contagion before it started. Banks did not understand the risks that LTCM was taking and over-extended credit at favourable terms which in turn encouraged more speculation. This modus operandi preceded the boom just before the collapse of Lehman Brothers. As a result, it's important for regulators, practitioners and academics to properly understand the characteristics of hedge funds, the drivers of their returns and their systemic importance to financial markets.

2.2 Generating and Chasing Alpha

The increasing prominence and dominance of hedge funds can be traced to the concept of '*Alpha'*. In the world of finance '*Alpha',* the Greek letter becomes a word that signifies an investment return that is due to the manager's skill rather than the performance of the broader market. Alpha is a code word for an elusive skill certain individuals are endowed with that gives them the ability to consistently beat the market by generating abnormal returns (Patterson, 2010).

A portfolio manager who earns 11% in a year whiles the major stock, bond, FX and commodity indices are up around 10% to 12% is considered to have achieved a '*beta'* return. Beta is shorthand for plain vanilla market returns. All portfolios could benefit from the rising tide of the markets. However, in a year where a portfolio gains 15% whiles the broader markets makes only 5% or even when the broader markets posts losses while the portfolio investor has such high positive returns is defined as 'Alpha'. By the end of 1990s, the massive development of complex quantitative and algorithmic trading along with a light touch regulatory system and endless financial innovation made the quest for this Holy Grail, i.e. the pursuit of alpha look insignificant and simple. Powerful players in the financial markets started undertaking complex strategies, investing in emerging-market bonds, Chinese stocks, oil-well partnerships, real estate, exotic financial products and commodities, chasing alpha returns.

Whiles mutual fund managers were struggling in bear markets such as those of 1980, 1987, 1990, 1994 and 2000; hedge funds had exposure to different assets which didn't follow these negatives patterns and continuously posted positive returns (Suzanne McGee. 2010)

2.2.1 What is Alpha and Beta?

Schneeweis and Spurgin (1996), Fung and Hsieh (1997), Weisman (2002), Jensen and Rotenberg (2003), Siegel (2004), Asness (2004a) and others have proposed innovative approaches that provide a powerful framework for separating and defining alpha and beta. Ineichen (2007) supports that 'alpha' in capital markets is already there but one should just take away all the various unwanted risks to carve it out. As markets become increasingly efficient, this will be extremely difficult using all the risk management tools available. Hedge funds do not hedge all risks in order to realize some asymmetric returns - generating Alpha consists of taking some risk. Different risks carry different returns. Ineichen (2007) states that some bets in the financial markets follow a Brownian motion (random walk) while others do not. The process of differentiating the two, the sculpting, is then a function of intelligence, savvy, effort, experience and skill. As proposed by C. Asness (2004), one should distinguish not between alpha and beta but between traditional betas, hedge fund betas and true alphas. Traditional betas refer to the traditional asset classes where a long-only strategy is sufficient to capture the yield or risk premium.

True alpha is a source of return that is entirely explained by the manager's investment skill and is not compensation of any systematic risk. Hedge fund betas are systematic risk premiums which require a slightly more sophisticated strategy than long-only strategies such as merger arbitrage, convertible bond arbitrage, statistical arbitrage or fixed income arbitrage. Many of these strategies would not be possible to implement without the tools of leverage, short-selling and financial derivatives. Asness (2004a and 2004b) proposed separating hedge fund alpha into: 1) beta exposure to other hedge funds and 2) manager skill alpha. Fung and Hsieh (2004) analyzed hedge fund returns with traditional betas and non-traditional betas which include trend following exposure and several derivative-based factors. They found that adding the non-traditional beta factors can explain up to 80% of the monthly return variation in hedge fund indices.

Lars Jaeger (2002) asserts there are risk premiums that are easily captured and others that are not easily captured depending on the investor skill. Asness (2003), Jensen and Rotenberg (2003), Dunn (2004) and Siegel (2004) make a similar observation. In the long-only world, market traditional beta is a well known strategy available to all with a justification of why it should achieve positive returns above the risk-free rate over time. Hedge fund betas follow a similar concept as the aforementioned. What these betas have in common is that they represent a known implementable strategy thus a source of potentially common systematic risk (Asness, 2004). Skill or alpha is simply the net return of these betas. The betas are exposures to strategies (traditional and hedge fund) which are known, common to many managers (so they explain a lot of common variation) and generally support why managers get paid (have positive expected returns over time). Alpha is what is left over. Inferring from Ineichen (2005), in order to separate alpha and beta, an alternative investment strategy is about performance being attributed to skill, i.e., alpha, while a long-only strategy is primarily a market-based strategy that is exposed to a market beta of some sort.

At this juncture, it's important to analyze the term Portable alpha which arises based on the notion that asset allocation and the search for alpha are separable. Edward Kung (2004) suggests that portable alpha enables investors to budget risk and improve alpha without dramatically changing asset allocation. Passive beta returns arise from any index fund exposure. Alpha returns come from security selection within a particular asset class. As a result, the excess return from a true alpha strategy does not depend upon the direction of the market. For example, a stock-picker would have a beta of 1.0 in comparison to their market benchmark and all the excess returns would arise from their "active risk" or stock picking. Portable alpha refers to the process of separating the alpha from the beta and then applying it to other portfolios (Edward Kung, 2004).

Finally, Asness (2004) notes that over time, as markets become more efficient, alpha can turn into beta. Thirty years ago, simply noticing and then implementing merger arbitrage or convertible bond arbitrage would seem to deserve tremendous credit and recognizing its attractiveness deserved to be called a skill. Nowadays, it seems far more likely that in its simplest form, it is a beta return.

2.2.2 Driver of Alpha returns

As hedge funds are evaluated on an absolute return basis, in order to be able to produce absolute returns irrespective of the general market direction, they should be able to short sell by taking full advantage of negative signals on stocks (see George Soros and John Paulson Case). However, they face numerous constraints in their search for Alpha because of the complexity in the financial markets and the huge competition between market participants. The hedge fund industry is also an interesting laboratory for examining local information effects partly because of its phenomenal growth (Teo, 2008). A whole cottage industry has emerged to help investors select ex-ante the hedge funds that deliver alpha growth (Teo, 2008). This industry includes hedge fund databases, hedge fund consultants, feeder funds and fund of funds. Investment banks are now churning out hedge fund replication products to help investors refocus their attention on alpha. However, the way hedge funds generate alpha, for the most part, remains a mystery. Based on the existing information, it seems natural that local information should explain some of the alpha returns and their variation.

Fung and Hsieh (1997, 2001, 2002, 2004a, 2004b), Agarwal and Naik (2004) and Hasanhodzic and Lo (2006) share the view that a large proportion of the variation in hedge fund returns can be explained by market-related factors. Agarwal and Naik (2004) and Fung and Hsieh (2004b) have reported hints of excess returns or alpha (cost and risk adjusted) from equity related hedge fund indices as empirical regularities with limited explanation as to the economic activities underlying the observed alpha. In a broader context, Kosowski, Naik and Teo (2007) reported persistent alpha returns across a broader spectrum of hedge fund strategies. Using funds of hedge funds as a proxy for diversified portfolios of hedge funds, Fung and Hsieh (2008) and Naik and Ramadorai (2008) reported similar results. Both papers investigated the persistency of observed alphas. Following the model of Berk and Green (2004), both studies confirmed the negative impact of a fund’s capital growth on its ability to deliver persistent alpha. Kosowski et al (2007) and Fung et al (2008) applied variants of the Fung and Hsieh (2004a) 7-factor model which was originally designed to substitute the general risk characteristics of diversified hedge fund portfolios. As a result, observed alphas at the level of specific style categories is a combination of risk model differences for that style category compared to the broad-based 7-factor model and other idiosyncratic sources.

Ibbotson, Chen and X. Zhu (2010) in order to measure the source of hedge fund returns calculated what portion of the returns arises from alphas, betas and costs. Their focus was on determining what portion of hedge fund returns are derived from traditional long beta exposures such as stocks, bonds and cash and what portion is from hedge fund alpha. Ibbotson, Chen and X. Zhu (2010) concluded that a portion of the hedge fund returns can be explained by non-traditional betas (hedge fund betas). However, these non-traditional beta exposures are not well specified or agreed upon and are not readily available to individual or institutional investors. An extensive portion of alpha can always be thought of as betas waiting to be implemented. However, since hedge funds are a primary way of gaining exposure to these non-traditional betas, they should be viewed as part of the value-addition that hedge funds provide compared to traditional open-end funds. Ibbotson, Chen and X. Zhu (2010) separated hedge fund returns using only the traditional stock, bond and cash beta exposures that are easily assessable for investors without hedge funds.

Finally, Edward Kung (2004) suggests that 'portable alpha' can be generated in many different ways using "leveraged" strategies which use very little cash for their margin requirement. Alternatively, he proposes strategies which purchase securities and use derivatives to remove market exposure. For example; a manager of small capitalization equities who generates 4% alpha each year can hedge the 'small cap' market exposure or beta by selling (shorting) some Index futures against the portfolio. That could result in a pure alpha return that can be applied to the overall fund.

2.3 Hedge funds Performance

2.3.1 Performance measurement and modelling of returns.

Back in the eighties, performance measures for investment funds were based on the Capital Asset Pricing Model (CAPM)[1], tools such as Jensen's[2] alpha (1968) and Sharpe's model (1964) and their extensions were commonly used in performance evaluation across different types of open-end and close-end funds. They were considered as the most accurate models for determining the abnormal returns of a security or a portfolio of securities. They had been created mainly to measure alpha returns in mutual funds but numerous researchers from the corridors of academia applied them to hedge fund performance evaluation. Subsequently, several multi-factor models have been created, including the 8-factor model developed by Grinblatt and Titman (1994), the asset class factor model by Sharpe (1992), the 3-factor model by Fama and French (1993) and the 4-factor model by Carhart (1997). Kothari and Warner (2001) assert that Fama and French's (1993) 3-factor model provides better results than the classical CAPM, however, they also suggest that it identifies significantly abnormal results (including timing) when they do not exist. Additionally, Carhart (1997) developed a four-factor model which proves to be superior in comparison to the classical CAPM, the Grinblatt and Titman (1989) 8-factor model and the Fama and French (1993) 3-factor model.

In particular, for hedge funds, different models have been applied in performance evaluation. Fung and Hsieh (1997) extended Sharpe's (1992) asset class factor model and found five dominant investment styles in hedge funds. The factors are specified as; value, systems/ opportunistic, global/macro, systems/trend-following and distressed. Schneeweis and Spurgin (1998) used style analysis-based methods on a multi-factor model. Brown et al. (1999) and Ackermann et al. (1999) used a single factor model and focused only on the total risk which hedge funds have exposure to. Agarwal and Naik (2000) used regression-based (parametric) and contingency-table based (non-parametric) methods. Liang (1999) uses the extension of Fung and Hsieh's (1997) model, regressions based on fund characteristics and classical measure such as the Sharpe ratio. Agarwal and Naik (2004) proposed a general asset class factor model comprising of excess returns on passive option-based strategies and on buy-and-hold strategies to benchmark the performance of hedge funds. Finally, Agarwal (2001) used a model consisting of trading

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1 A financial model, introduced by Jack Treynor (1961, 1962),[1] William Sharpe (1964), John Lintner (1965a,b) and Jan Mossin (1966) independently, building on the earlier work of Harry Markowitz on diversification and modern portfolio theory. It was created to determine a theoretically appropriate required rate of return of an asset in a well-diversified portfolio. The model takes into account the asset's sensitivity to non-diversifiable risk often represented by the quantity beta (β), as well as the expected return of the market and the expected return of a theoretical risk-free asset.

2 Performance measurement model for investment funds

strategy factors and location factors to explain the variation in hedge funds returns over time. These results suggest that it is necessary to realize performance studies based on multi-factor models, rather than simply use the classical CAPM; however the ideal model does not really exist.

2.3.2 Drivers of Returns and Factor Selection

Since Sharpe's first performance measurement model in 1964 for open-end investment funds, manipulations have been made. In 1992 came an extended quantitative model applied specifically to hedge funds. The extended Sharpe's (1992) formula is outlined below:

$$Rt = \alpha + \sum_{K} \beta k \; Fkt + \varepsilon t$$

Where Rt is a funds return at time t, the Fkt variables are for the style factors, the βk variables are the systematic market factors and εt is the residual. His measure compares the fund return via the fund beta with the return on a benchmark portfolio. If the average fund return is significantly higher than expected given the fund beta and the average benchmark return, superior performance is implied. Similarly, Jensen's alpha is easily calculated by performing a standard OLS regression of the fund return on the benchmark return. The intercept of the regression line is Jensen's alpha.

Hedge fund returns can be characterized more generally by three key determinants; the returns from assets in the manager's portfolios, the dynamic trading strategies and the level of leverage. Hedge fund returns have low and sometimes negative correlation in comparison to traditional asset class returns such as equities, bonds, currencies and commodities. The behaviour of hedge funds was firstly investigated by Fung and Hsieh (1997) who employed a Sharpe multi-factor model to investigate the behaviour of hedge fund returns relative to the ''style'' factors of mutual funds as noted earlier. They uncovered that nearly half of the hedge funds have negative betas[3]. They argue that hedge fund managers employ different styles in comparison to open-end fund managers[4] and also modified their trading strategies. Thus hedge fund managers undertake dynamic trading strategies whereas most open-end fund managers engage in simple buy-and-hold strategies. Additionally, they employed a multi factor model to identify statistically important dimensions in hedge fund returns. As part of the study, the authors regressed these factors against the eight mutual fund style factors and found that the overall explanatory power of the eight style factors is incomplete. They incorporate additional factors that are designed to capture the returns from highly leveraged trading strategies from the use of options and from a junk bond return index. The

[3] This hypothesis will be rejected and it will be proved in the analysis afterwards that this is not the case anymore over the last 5 years.

[4] Referring to structured investment vehicles such as mutual funds

resulting 12-factor model explains a much higher proportion of hedge fund returns than the open-end eight-factor style model. Fung and Hsieh (1997) conclude that hedge fund managerial flexibility allows them to combine traditional "relative return" investment approaches from the open-end fund industry with additional strategies to construct "absolute return" investment styles. This produces rates of returns that are uncorrelated with the standard style factors that drive open-end returns. Barès, Gibson and Gyger (2001) used clustering techniques to devise a style consistency test and found that many hedge fund managers do not follow a consistent investment strategy. Finally, Agarwal et al (2004) assert that hedge fund returns exhibit a higher proportion of variance. They suggest that there is a non-linear payoff for many complex hedge fund strategies. Non-linear return models suggest that investors in hedge funds are statistically exposed to greater chances of extreme returns. Nonetheless, many hedge funds also exhibit substantial market (beta) risk.

2.3.2.1 Which factors should be considered?

Multi-factor models could be very effective in order to obtain information with regards to the key drivers of hedge fund returns. However, the major complication is the accurate choice and identification of relevant factors. Sharpe (1992) used 12 global stock and bond indices to describe the cross sectional[5] returns of U.S. equity funds. His factors included government bills, Large-Capitalization Growth Stocks, Intermediate-term Government Bonds, Medium-Capitalization Stocks, Long-term Government Bonds, Small-Capitalization Stocks, Corporate Bonds, Non-U.S. Bonds, Mortgage-Related Securities, Large-Capitalization Value Stocks, European Stocks and Japanese Stocks. Elton, Gruber and Blake (1995) chose a series of macroeconomic variables for U.S. bond funds. However, the case could be much different for alternative investment vehicles as they have the choice to invest in a much greater variety of assets, liquid or illiquid, uncorrelated with traditional asset classes; they have access to leverage, the ability to undertake short selling and the technology to engage in computerized trades in a matter of milliseconds. Irwin et al. (1994) in their single factor model used a simple managed futures benchmark and McCarthy et al. (1997) suggested a single index with Bayesian adjustment for leverage. Mitev (1995) in his multi factor model suggested five implied factors, identified as trend following strategies, stop-loss control models, agricultural markets, interest rate spread-strategies and global macroeconomic factors. Liang (2000) relied on eight asset classes including the S&P 500, MSCI world, MSCI emerging, global government and corporate bond indices, Federal Reserve Bank trade weighted dollar index, gold price and one-month Eurodollar cash deposit. Finally, Schneeweis and Spurgin (1998) combined a very large number of hedge fund indices, CTA indices and traditional asset class indices. All these models relied on

[5] Cross-sectional data refers to data collected by observing many subjects (such as individuals, firms or countries/regions) at the same point in time or without regard to differences in time.

a regression analysis. Appendix 3 provides a summary of correlated factors (negative and positive) which have been identified by academics and practitioners as key drivers of hedge fund returns.

2.3.3 Survivorship Bias

Measuring the performance of hedge funds is very complicated because funds submit data to several hedge fund databases regarding their return figures and their style but they do not provide them with any details about the structure of the underlying strategies, their risk management methods and the correlations of their investments with particular broad market indices. Research demonstrates that a pronounced inflation of returns can result if survivorship bias is not addressed. Hedge fund databases provide only information on hedge funds that are still alive. However omission of dead funds when computing returns of a portfolio (or index) of funds increase biases in performance measure and does not reflect the true return earned by an investor who would have invested in all funds available at the beginning of the period (alive and dead funds at the end of the period). Therefore, this bias is significantly larger for the TASS dataset which includes more offshore funds than the Hedge Fund Research Inc. (HFR) dataset and it can be as much as 3% yearly (Anderson et al.2010). The disappearance of funds from hedge fund databases has been the focus of significant research. Evidence indicates that disappearing funds close down and distribute their funds back to their investors; they do not just stop reporting. Reasons behind hedge fund exits are numerous but the most common appears to be poor performance, diminished economies of scale or withdrawals and personal reasons such as the retirement of partners (Anderson et al. 2010). Liang and Bing (2000) report that the HFR database contains an extremely low survivorship bias of about one-third to one-eighth of the rate reported for open-end funds. In contrast, the TASS database rate is significantly higher at 2.24% in comparison to the 0.16% reported for HFR. Liang suggests that this is partly because the TASS database contains more off-shore funds. However, he concludes that HFR contains a much lower number of dissolved funds thus significantly overstates returns for the hedge fund industry, especially for the pre-1994 period. His empirical evidence suggests that the primary reason for the dissolution of hedge funds is inferior performance. Liang (2000) concludes that younger and smaller hedge funds experiencing poor returns are the most likely candidates to dissolve.

2.3.4 Performance Persistence

Edwards (1999, p.189) notes, ‘‘It is hard to imagine a gr*eater misnomer than ‘hedge fund’,* since hedge funds typically do just the opposite of what their names implies: they speculate.’’

Edwards F. (1999) presents three hypotheses for the existence and growth of hedge funds. The low correlation in fund returns with broad market indices, the ability of incentive fees to attract high quality management and the ability of hedge funds to engage in high-risk strategies which produce high rates of return. Edwards concludes that hedge funds have achieved historic returns that are virtually uncorrelated with broad market indices such as the S&P 500. This statistical independence suggests that hedge funds have an economically significant role to play in the diversification of large portfolios. He asserts that hedge funds engage in novel strategies which are far riskier than those that traditional empirical measures such as beta would suggest.

In classical finance theory, the post-fee abnormal performance of top hedge funds is driven purely by sample variability and hedge fund performance does not persist. The efficient markets hypothesis of Eugene Fama also supports that markets are too efficient to produce consistent abnormal Alpha returns. Before moving on to the academic evidence for this issue, a personal note here would question the above assumption. A key personal query about the above assumption would be how trailblazers in the field ‘Quants’ investing such as Peter Muller, Ken Griffin, Cliff Asness, Boaz Weinstein, Jim Simons, Ed Thorp and other well-known Math and Physics professors developed powerful Wall Street investment houses (AQR, Renaissance Technology, Citadel, PDT, Global Alpha etc) back in 80s and 90s were able to consistently beat the markets year–on-year employing powerful computerized machines, algorithms and ingenious exotic strategies driven by scientists and a wide range of scientific fields? However, this particular assertion could be highly controversial. One cannot be drawing such conclusions because of several extreme events and performances. The aforementioned top hedge fund managers are not enough to conclude that their abnormal returns all these years were statistically significant with the remaining hedge fund industry because the sample analysis which is conducted by most researchers includes more than 4000 funds.

Agarwal and Naik (2000) suggested that hedge fund returns only persist in the short term (one to three months). They examined the hypothesis that hedge fund managers employ restricted liquidity of invested funds to adopt trading strategies that yield significant multi-period returns and tested if a profitable hedge fund in one particular period will back that trend in the subsequent period. By employing Jensen’s alpha and the appraisal ratio constructed models, it was found that the most persuasive case for performance persistence is on a quarterly basis with pre-fee income. They found no persistence in yearly returns. Getmansky, Lo and Makarov (2004) credit that to the illiquidity induced by assets that hedge funds trade. Agarwal and Naik (2000), Brown, Goetzmann and Ibbotson (1999) and Liang (2000) found no evidence of persistence in hedge fund returns at annual horizons.

However, Brown, Goetzmann and Ibbotson (1999) and Ackermann, McEnally and Ravenscraft (1999) applied a single factor model and found that hedge funds produce positive abnormal returns. They also found that hedge funds produce high return with low systematic risk in comparison to mutual funds and that equally-weighted and value weighted hedge fund indices generate higher Sharpe ratios and Jensen's alphas. They uncovered that Jensen's alpha[6] is significantly positive in all hedge fund samples. Other studies are carried out using both single and multi-factor models. The multi-factors usually include major equity and fixed income indices and/or factors since hedge funds are mostly multi asset vehicles and trade almost everything, from equity to fixed income instruments in both domestic and emerging/international markets. Liang (1999), Kazemi and Schneeweis (2004) used multi-factor models in their studies because this enabled them to explain return variability in hedge funds. Kat and Miffre (2002), Amenc and Martellini (2003) and Kazemi and Schneeweis (2004) applied conditional[7] multi-factor models which lead to the conclusion that hedge funds generate positive alphas. Kat and Miffre (2002) used linear single- three- and six- factor models hinged on public information variables in order to capture time varying expected return. They uncovered that the significance of alpha increases with the conditional model. Kazemi and Schneeweis (2004) applied a conditional stochastic discount factor model in combination with single and multi-factor models to hedge fund indices as well as to hedge fund managers.

All of these models concur that both hedge fund indices and hedge fund managers produce positive risk-adjusted excess returns. Edwards and Caglayan (2001) however found important evidence for performance persistence in both winners and losers over one- and two-year horizons. Kat and Menexe (2002) found that while there is little evidence of persistence in mean returns, the standard deviation of returns are strongly persistent and skewness and kurtosis are weakly persistent.

Melvyn and Narayan (2010) by using powerful bootstrap and Bayesian methods documented evidence of long-term performance persistence with hedge funds show that the abnormal long term performance of top hedge funds cannot be attributed to luck and that hedge fund abnormal performance persists at annual horizons. Evidence also suggests that hedge funds which achieve abnormal positive performance are likely to continue to earn positive alphas in future periods. Hedge funds display tactical asset allocation skills, especially by reducing beta exposures to the market in bear markets (see appendix

[6] A measure used to determine the abnormal return of a security or portfolio of securities over the theoretical expected return.

[7] Conditional set of variables contemporaneously with the dependent variable (returns).

4). For example, the estimated stock beta exposure was lowest during the 2000-2002 bear market period. Ibbotson, Chen and X. Zhu (2010) found that Hedge Funds did not avoid the beta exposure in 2008 nor fully participate in the 2009 market but nonetheless kept their positive alpha throughout the financial crisis of 2008 and 2009. Alpha during the entire period was significantly positive and hedge fund alphas stayed positive from year to year. Alpha was positive for all years with the exception of 1998. This indicates that the average hedge fund manager added value in both bear and bull markets. Additionally, hedge funds did not substantially reduce their beta in 2008, earning a negative return for the year. However, hedge funds continued to produce positive alpha in both 2008 and 2009 thus continuing an eleven year of unbroken string of positive alphas (Ibbotson, Chen and X. Zhu, 2010). Furthermore, profitable hedge fund managers are more likely to experience significant inflows of new capital than managers with negative performance. Hedge funds grow more rapidly than open-end funds, but they shrink faster as well because they are exposed to much more leverage and risky strategies (Anderson et al.2010).

2.4 Strategies

Very often, one would observe that there is wide dispersion of returns among hedge funds which follow the same strategy. The reason is that traditional asset classes such as equities, bond, currencies and commodities have an economic rationale behind their mean returns. On the other hand, hedge funds have no economic rationale behind their performance. There are no standard risk premiums in the classic economic sense, apart from what is known with regards to hedge fund beta and alpha. Their returns are achieved by the fund manager's ability to exploit inefficiencies which other investors have not observed or they are unable to do so. Predictability of some sort is important when a favourably skewed risk/reward trade-off is the objective (Alexander M. Ineichen, 2005).

In the mid 1990s, famous 'Quants' such as Ken Griffin, Ed Thorp, Jim Simons, Cliff Asness, Boaz Weinstein and Peter Muller were all building lucrative quantitative strategies, conducting complex mathematical algorithms and their funds were beating the markets consistently. Each of their quantitative houses was becoming part of and helping to create a massive electronic network, a digitalized and computerized money-trading mechanism that could transfer billions globally in the blink of an eye (Patterson, 2010). On the other hand, there were also numerous hedge funds focused mainly on less quantitative strategies and conducting mainly macroeconomic and microeconomic research and undertaking certain bets which would maximize their returns.

The four dimensions of hedge fund classification according to the TASS model are; asset class, investment bias, trading style and geographical focus. Furthermore, it is possible to divide strategies into non-directional and directional (Vikas Agerval, Narayan Y. Naik, Burki, 2000). Non-directional strategies are known as market neutral strategies where fund managers seek to capitalize on gains while keeping market exposure to a minimum. Their trademark is low correlation with markets and entails exploiting arbitrage opportunities and structural discrepancies via identifying mispricing and market inefficiencies. Directional strategies are also known as market-timing strategies. Typically, these strategies are more strongly correlated with markets and involve fund managers timing the market and betting on movements (Jakobsons, 2002).

Strategies also differ considerably within these boundaries and a particular strategy can also be implemented differently to deliver varied levels of market correlation. Hedge funds in general yield returns that have a low correlation with the market but a non-directional strategy can be perceived as less aggressive hence a more prudent strategy. Returns are normally more stable and have a very low correlation to the market. Directional strategies are of a more opportunistic nature; returns are more varied and can be sensational. In addition, experienced hedge-fund investors and managers distinguish between "statistical arbitrage", "quantitative equity market-neutral" and "long/short equity" terms for main category strategies (Khandani and Lo, 2007). The first category refers to highly technical short-term mean-reversion strategies that consist of a large number of securities, very short holding periods (measured in seconds to days) and considerable computational, trading and IT infrastructure. The second category involves broader types of quantitative models, some with lower turnovers, smaller amount of securities and inputs other than past prices such as accounting variables, earnings forecasts and economic indicators. The third category is the broadest and is made up of equity portfolios that engage in short selling and that may or may not be market-neutral and quantitative and where technology need not play an important role.

To highlight some of the differences, directional strategies are characterized by being more aggressive but this may not be true in some individual cases. Since there are limited industry standards in defining different strategies, it is better to define the broader categories which are employed in this paper. The analysis is partially based on several sources including Deutsche Bank's interpretation of the hedge fund universe, Fothergill (2000), Fung & Hsien (1997, 1999, 2001, 2002, 2004), Schneeweis & Spurgin (1998), Agarval & Y. Naik (2000), Cottier (2000), Asness (2001, 2004), Scott Patterson (2010), Connor and Lasarte (2003) and Inechien (2000). It will also include contributions from academics and other industry professionals presented in Table 2.

Equity Hedge - Long/Short Equity **–** The directional strategy seeks to take advantage of undervalued and overvalued securities by engaging in long and short positions of the market. Managers can be net long or short, value or growth, small or large cap and they may use different derivatives such as futures and options to hedge their risks. The focus may be regional, such as long/short U.S or European equity or sector specific such as long and short technology or healthcare stocks. Long/short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds. The strategy might also cover a multitude of sub strategies which mainly are divided up by their net exposure and geographical focus e.g. from Domestic Long Equity to Emerging Markets. Managers commonly use leverage and levels of opportunism vary considerable. An alternative of this strategy is the 'pairs trading' which consists of the combined purchase and sale of two similar securities where one is overvalued relative to the other. As soon as the market corrects itself, this should yield a positive payoff as the prices of the two securities equalized, irrespective of movements in the general market. Pairs trading can be applied in other asset classes. Pairs trading are related to a famous strategy called Statistical Arbitrage Ross (1976). The statistical arbitrage seeks to exploit any pricing discrepancy that exists between related securities while hedging against all risk exposures such a market risk, sector risk and factor-related risk and diversifying asset-specific risk.

Market Neutral – Here the manager tries to generate alpha returns while eliminating systematic risk. There are a number of different specifications of this general strategy. The most widely used is Equity Market Neutral, which is designed to exploit equity market inefficiencies and entails being simultaneously long and short in matched equity portfolios of the same size within a country. This strategy is related to the concept of portable alpha. Market neutral portfolios are designed to be either beta or currency neutral or both. Well-designed portfolios typically control for industry, sector, market capitalization and other exposures. Leverage is often applied to enhance returns. The manager seeks to benefit from both alphas created while remaining beta neutral. The strategies can become much more complicated and sophisticated than exemplified here and may be based on "black box" mathematical systems. This is particularly present in similar market neutral strategies based on arbitrage, namely; Convertible Arbitrage, Fixed Income Arbitrage, Structure Arbitrage, Derivatives Arbitrage and Equity Index Arbitrage. Investment funds hedge their exposure to the price movements of the underlying securities, interest rates and broad market movements. Since relative value price discrepancies tend to be small, hedge funds operating in this area tend to be among the most leveraged, in order to magnify potential gains. Convertible arbitrage, one of the most successful lucrative trading strategies ever devised consists of investing in the convertible securities of a company. A typical investment is to be long on a convertible bond and short on a common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of the stock while protecting the principal from market moves. Fixed income arbitrage consists of profiting from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, U.S. and non-U.S. government bond arbitrage, forward yield curve arbitrage and mortgage-backed securities arbitrage. However, Patton (2004) questions hedge funds which claim they are market neutral by distinguishing between market neutrality which is defined as zero correlation with the market return and "complete neutrality" defined as no dependence between the hedge fund return and market index return. Patton suggests that empirically, about a quarter of self-described market neutral hedge funds are not in fact market neutral.

Global Macro – This strategy employs an opportunistic and speculative top-down approach in order to take advantage of market movements through long and short positions. The investment process is based on macroeconomic analysis and forecasts in global interest rates, currency and equities markets and policy changes. Market participants will take into consideration a diverse set of factors such as geopolitical issues, economic indicators, market trends and liquidity flows. A variety of financial instruments, markets, sectors and trading styles are employed and the usage of leverage is high. Being one of the most directional of strategies, it is also very risky but returns are not necessarily strongly correlated with the overall market. Global Macro funds were made famous by high profile investors who achieved extraordinary returns over time such as George Soros. They carry long and short positions in the world's major capital or derivative markets with portfolios of stocks, bonds, currencies, commodities and derivatives instruments in developed and emerging markets. These positions reflect their views on overall market direction as influenced by major economic trends and/or events. The strategy relies on the ability to make superior forecasts compared to other market participants and act quickly and decisively.

Event Driven – This strategy focuses on special corporate situations and events that are expected to make an impact in the short run such as M&As, corporate restructuring, stock buybacks, bankruptcies, bond upgrades, earnings surprises and spin-offs. The principle risk factor becomes the deal rather than the market as the strategy consists of investing in companies that are involved in such situations and typically would take a long position in the target and simultaneously short the acquirers in an M&A deal (Merger Arbitrage). The Distressed Securities strategy is more directional due to the financially unstable nature of the underlying financial instruments such as bonds, stocks, bank debt, trade claims, private placements and warrants. This strategy is defined as 'special situations investing' and is designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization.

Short Selling – Funds which take on short positions in equity, put options and other derivatives products employ the short selling strategy. They always have a short bias greater than zero and seek to benefit from overvalued individual companies and bearish markets. Throughout the 1990s bull market, short sellers almost disappeared but have recently emerged again as an alternative strategy. Dedicated short sellers were once a robust category of hedge funds before the long bull market rendered the strategy difficult to implement. Short biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category. John Paulson became a famous short seller by earning $20 billion after his smart bet using Credit Default Swaps against the real estate and subprime bubble, mainly by shorting (CDS trade) the toxic Collateral Debt Obligations and other Asset Backed Securities.

Multi-Strategy - The funds in this category are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge fund disciplines. The use of many strategies and the ability to reallocate capital between them in response to market opportunities means that such funds are not easily assigned to any traditional category.

Fund of Funds – This approach involves a hedge fund investing in other external hedge funds. Managers create a diversified portfolio of different funds to produce consistent returns with a minimum risk. Fund of funds provide better access to experienced management, enhanced liquidity and less risk of default. However, due diligence, transparency and easier access comes with additional layers of fees. Investment fund units could also be considered very illiquid and exit from these investments can prove rather impossible.

2.5 Summary of the academic research and key trends

The above theoretical analysis and literature regarding the three key main focus issues - strategies, performance and Alpha returns is summarized on the two tables below:

Table1

Four global categories of hedge fund academic studies:

HEDGE FUND PERFORMANCE	HEDGE FUND INVESTMENT STYLE/STRATEGIES	CORRELATION ANALYSIS AND DIVERSIFICATION POWER	OTHER STUDIES
- Comparison with traditional asset class (Ackermann et al., 1999; Brown et al., 1999; Liang, 1999; Amin and Kat, 2001; Liang, 2001; Barès et al., 2002; Liang, 2003; Agarwal and Naik, 2004).	Sharpe style analysis (Fung and Hsieh, 1997; Brown et al., 1998; Brealy and Kaplanis, 2001, Brown and Goetzmann, 2001, Liang 2001; Ben Dor and Jagannathan, 2002; Liang 2003).	- Correlation analysis (Fung and Hsieh, 1997; Schneeweis and Spurgin, 1997; Liang, 1999; Agarwal and Naik, 1999).	Risks (Schneeweis and Spurgin, 1999; Jorion, 2000; Amenc et al., 2002a; Amenc et al., 2002b, Berényi, 2002). - Bias analysis (Liang, 2000; Fung and Hsieh, 2000. (Khandani and Lo, 2007)
Comparison with mutual funds (Ackermann et al., 1999 and Liang, 1999).	Fothergill (2000), Fung & Hsien (1997, 1999, 2001, 2002, 2004), Schneeweis & Spurgin (1998), Agarval & Y. Naik (2000), Cottier (2000), Asness (2001, 2004), Scott Patterson (2010), Connor and Lasarte (2003) and Inechien (2000)	- Diversification power (Amin and Kat, 2001; Amenc and Martellini, 2002).	- Hedge fund indices (Brooks and Kat, 2001; Amenc and Martellini, 2002; Fung and Hsieh, 2002b).
- Persistence in performance (Agarwal and Naik, 2000; Brown et al., 1999; Hübner and Papagergiou, 2006; Liang 2001; Liang, 2000).	- Dynamic model (Swinkels and Van der Sluis, 2001; Posthuma and Van der Sluis) - Rolling regression (McGuire, Remolona and Tsatsaronis, 2005).		- CTAs (Edwards and Park, 1996; Fung and Hsieh, 2001; Gregoriou and Rouah, 2003; Liang, 2003; Spurgin and Georgiev, 2001).

Table 1 groups studies on hedge fund performance, hedge fund investment style, correlation analysis, diversification power and finally the other studies.

Table 2

Categorizations of hedge fund strategies and differences from academics and practitioners:

William Fung & David A. Hsien	Thomas Schneeweis & Richard Spurgin	Vikas Agerval & Narayan Y. Naik	Phillip Cottier	TASS/Tremont.	RR Capital/KPMG/ Credit Suisse fund index
Convertible arbitrage Distressed securities Emerging markets Equity hedge Equity market neutral Equity non-hedge Event driven Fixed income Macro Market timing Merger arbitrage Relative value arbitrage Sector Short Selling Statistical Arbitrage	**Relative value** - Equity market neutral - Convertible hedge - Bond hedge **Event** - Merger arbitrage - Bankruptcy - Multi-strategy **Equity hedge** - Domestic long - Hedged equity - Global / international **Global** - Discretionary - Systematic - Short	**Non-directional Strategies** - Fixed income arbitrage - Event driven - Equity hedge - Restructuring - Event arbitrage - Capital structure arbitrage **Directional Strategies** - Macro - Long - Hedge (long bias) - Short	Leveraged long equity Short-only equity Long/short US equity Long/short European equity Long/short global equity Leveraged bond and fixed income arbitrage Mortgage-backed securities arbitrage Convertible bond Distressed securities Emerging markets Macro Currency Multi-strategy Multi-manager	Market neutral Convertible arbitrage Global macro Growth Value Sector Distressed securities Emerging markets Opportunistic Leveraged Bonds Short Only	Long/short equity Convertible arbitrage Event driven Equity market neutral Equity trading Global macro Fixed income arbitrage Dedicated short bias Emerging markets Managed futures Fund of funds Multi strategy

Table 2 groups all the identification and the categorizations of hedge fund strategies from academics and professional research institutions.

It’s interesting to observe how the Industry Trends Strategy has changed over the last two decades for hedge funds. The macro strategies decreased significantly and the event driven strategies enjoyed a huge increase. This could be attributed to technological advances and quantitative developments which have provided opportunities for speculation in strategies such as merger arbitrage and distress securities trading.

2.6 Market Impact to the global financial markets

Hedge funds are frequently at the centre of attention when there is high volatility in the financial markets because of potential short selling, high frequency trades, macroeconomic bets, large commodity trading and highly leveraged strategies. Success involves hedge fund bets against a currency or a market after which they collapse in value leading to very large profits for the hedge fund (see George Soros and John Paulson). As a result, many academics, politicians, analysts and economists argue that hedge funds cause contagion and distress in the marketplace from which they ultimately profit. However, academic evidence does not support the view that hedge funds can manipulate markets to an extent that they earn large returns at the expense of small investors.

Admittedly, returns to individual hedge funds can at times be spectacular in a short period of time. In 1992, the financial world was riveted by news that the Quantum Group had earned as much as US $1.8

billion by shorting the British pound and going long on the Deutschmark (Anderson et al. 2010). However, several years later, this event was overshadowed by the dramatic collapse of the Russian rouble, which led to a US $2 billion loss by the Quantum Group and which also led to a Federal Reserve-orchestrated bailout of Long-Term Capital Management after its US $4 billion loss (Anderson et al. 2010). The intervention of the Federal Reserve was highly debated, however cooler heads prevailed and a wide-spread contagion was avoided. Consequently, the industry was developing a bad reputation in the eyes of the general public – aided by the vacuum of public information caused by the lack of reporting. The decline in security prices that accompanied the collapse of the subprime mortgage market in 2007 led to the closing of a number of hedge funds. The spectacular $20billion gain John Paulson achieved as he foresaw the madness of the sub-prime market and the accompanying securitization business when everybody was mesmerized by the global economic boom proved that speculators didn't really affect anything in the 2007 crash. The crash was inevitable and the fundamentals of the banking and real estate markets were unsustainable and so John Paulson made his bet from 2006 when it was considered as an unsustainable debt.

2.6.1 Historical examples

Fung and Hsieh (2000) examined the potential role that hedge funds played in major market events during some macro turbulence: the 1987 stock market crash, the 1992 European Rate Mechanism (ERM) crisis, the 1993 global bond rally, the 1994 bond market turbulence, the 1994–1995 Mexican crisis and the 1997 Asian currency crisis. They assessed the rates of return for various hedge fund styles and compared that with various market return indices. The evidence suggests that hedge funds were active in the 1992 ERM crisis, the 1993 global bond rally and the subsequent decline in the bond market in 1994; however they didn't contribute to the price momentum and variance during these periods in the 1990s, and they concluded that hedge fund activities were prominent and probably exerted market impact during several episodes; There was no evidence that hedge funds applied positive feedback trading in any of these episodes; There was no evidence that hedge funds deliberately gave signals to other investors to engage similar market positions. Almost contemporaneous with the Asian currency crisis of 1997 were calls that the speculative activities of hedge funds (in particular George Soros') were either a causal factor or a contributing factor to the crisis. Brown, Goetzmann and Park (2000) employed a Sharpe (1992) returns-based style analysis with currency variables to determine if hedge fund returns ‘‘load’’ on the currency factors, thereby reducing fund exposure. Evidence did not show any negative positions in the Malaysian currency and the net short positions of the funds were declining during the sharp decline of the ringgit. Thus, the funds were buying-in their short positions during this time. Such transactions would have helped to curtail the fall in the ringgit rather than to contribute to it (Brown et al, 1997). While numerous academics may have warned that systemic risk in the hedge-fund industry has been on the rise (Carey and Stulz, 2006), none of the academic literature has produced any timely forecasts of when and how such shocks might occur or how they affect the financial markets.

2.6.2 What happened to the 'Quants' in 2007

If history has proven anything, it's that patterns repeat, again and again. Greed takes over and the self-fulfilling groupthink of the herd trumps rational process. From the book Diary of a Hedge Fund Manager by Keith McCullough and Rich Blake

The line goes, 'when America sneezes, the world catches a cold'. The global recession of 2007-09 was triggered by the decline of real estate prices, the bursting of the subprime-mortgage bubble and the collapse of Lehman Brothers, all originating in the United States. These factors combined resulted in the collapse and decline of credit markets and asset prices worldwide along with the sharp deterioration of the fiscal accounts of most developed economies and corporations. Investors in the credit markets responded to the situation by driving up credit spreads. Credit markets froze, inter-banking lending (commercial paper) also stagnated and banks were reluctant in lending to companies or individuals or even to huge corporations such as Microsoft, IBM, General Electric and GM (Logothetis, 2011). The global financial system was unable to provide liquidity for the real economy and itself. After the catastrophic bankruptcy of Lehman Brothers, one of the most powerful investment banks in the world, governments and economists concluded that any corporation or financial institution in the world wasn't powerful and big enough to avoid failure. In turn, the U.S government decided that some corporations were 'too big to fail'. As a result, Henry Paulson, the United States Treasury Secretary, stepped up to bail out the whole financial system via the Trouble Asset Relief Program in order to clear bank's balance sheets of toxic assets (asset backed securities, subprime liabilities etc.) (Logothetis, 2011). The US government provided funds from taxpayers to Wall Street giants such as Goldman Sachs, JP Morgan and other financial institutions. It nationalized Citigroup, Freddie Mac, Fannie May, American Insurance Group and General Motors. Other governments in the world followed the same steps such as the United Kingdom where Gordon Brown nationalized the Royal Bank of Scotland and Northern Rock, the biggest mortgage lenders in the UK. The Governor of the Bank of England, Mervyn King, rather poignantly noted *'Never has so much money been owed by so few to so many'* (Guardian, 2008). All the above events led to the biggest global recession in human history after 1930s.

Just one year before the collapse of Lehman brothers, the first signs of the turmoil at the financial markets were severe. The collapse of two Bear Stearns credit strategies funds in June, the sale of Sowood

Capital Management's portfolio to Citadel after losses exceeding 50% in July and the mounting problems at Countrywide Financial throughout the second and third quarters of 2007 set the stage for further turmoil in fixed-income and credit markets during the month of August. Hedge fund strategies began to make significant amount of losses mainly due to the high levels of leverage. Hedge funds rely on leverage and as such the size of their positions is often significantly larger than the amount of collateral used to support these positions. While leverage is able to multiply and expand small profit opportunities into larger ones, it works vice versa when adverse changes in market prices reduce the market value of collateral. Therefore, credit is withdrawn quickly and the subsequent sudden liquidation of large positions over short periods of time can lead to contagion and financial panic. As a result, massive losses in August 2007 were caused by the unwinding of large equity market-neutral portfolios and any explicit factors used to construct such portfolios would have generated a loss for other portfolios with the same factor exposures (Khandani and Lo, 2007).

A sudden liquidation of a quantitative equity market-neutral portfolio could have far broader repercussions, depending on the portfolio's specific factor exposures (Khandani and Lo, 2007). At that time, i.e. in 2007, the affected funds curtailed their risk by reducing their exposures or deleveraging because they exceeded the borrowing and risk limits of their brokers and creditors. That seemed to be disastrous. Over the last 15 years, every time the market lurched too far out of equilibrium, supercomputers raced to the rescue, gobbling up mispriced securities and restoring stability in the markets (Patterson, 2010). However in the summer of 2007, the unfortunate coordinated efforts of many funds to reduce their risk exposure simultaneously led to massive losses and indices such as the S&P500 were in a free fall. There was a complete reversal of quant strategies, where bad assets rose and good assets fell, ignited by a mass deleveraging of funds with overlapping strategies. It was an entirely new event, with strong statistical properties unlike any that had ever been seen in the past, i.e. ‘Black Swan’ event.

Mandelbrot (1963) stated that over long periods, equilibrium tends to rule the day. However, prices can gyrate wildly over short periods of time, wildly enough to cause massive potentially crippling losses to investors who made large leveraged wagers (Patterson, 2010). Therefore, severe losses caused due to unexpected liquidity-motivated quick trades and information asymmetries between market players in large block of securities and not by any fundamental change in the equilibrium returns of long/short equity strategies would apparently have had a significant impact on price levels. If there existed information that such significant short term price changes were not based on information but merely on a scramble for liquidity, prices would tend to readjust to their previous equilibrium levels. This partial-adjustment property of the price-discovery process is one compelling reason for “sunshine” trades - the practice of pre-announcing a large trade so as to identify oneself as a liquidity trader with no proprietary information, so as to reduce the price impact of the trade (Admati and Peiderer, 1991). The common factors driving these strategies suddenly became a significant source of risk and the "phase-locking" behaviour described in Lo (2001) apparently can cause as much dislocation of prices in long/short equity strategies as in other parts of the hedge-fund industry.

2.6.3 Concluding remarks

The truth is that hedge funds became similar to entities such as banks and the reason that the banking industry is so highly regulated is because of the enormous social externalities which banks might generate when they fail. However, hedge funds are able to withdraw liquidity at a very short notice, mostly rarely and randomly, but synchronized withdrawals of liquidity among an entire sector of hedge funds could have disastrous consequences for the viability of the financial system (Khandani and Lo, 2007). In other words, a scramble for liquidity may entail meltdown risks for the financial system (Nicholas Crafts, 2008). The increase in the number of funds and the average assets under management, the increase in average absolute correlations among the hedge-fund indexes and the growth of credit-related strategies among hedge funds and proprietary trading desks suggest that systemic risk in the hedge-fund industry may have increased in recent years. As can be observed from table 3 below, problems in the sub-prime mortgage and credit sectors triggered liquidity shocks in the more liquid hedge-fund style categories such as long/short equity, global macro and managed futures (Khandani and Lo, 2007).

Table 3: CS/Tremont hedge-fund index returns for the month of August 2007.

Index / Sub Strategies

Credit Suisse/Tremont Hedge Fund Index	-1.53%
Convertible Arbitrage	-1.08%
Emerging Markets	-2.37%
Equity Market Neutral	-0.39%
Event Driven	-1.88%
Distressed	-1.73%
Multi-Strategy	-2.03%
Risk Arbitrage	-0.65%
Fixed Income Arbitrage	-0.87%
Global Macro	-0.62%
Long/Short Equity	-1.38%
Managed Futures	-4.61%

Source: www.hedgeindex.com.

3 A Quantitative Approach in the corridors of the Industry

3.1 Databases

The 1997 Asian crisis, the 1998 Russian crisis, the 1999 Brazil crisis, the year 2000 Internet bubble burst and the collapse of Long Term Capital Management LP in 1998 raised serious concerns for credit providers, trading, counterparties and market regulators. Investors require more effective oversight of their assets and banks, investment consultants and funds of hedge fund managers require access to information for hedge funds' risk and return profiles. Additionally, the huge growth in the number of hedge funds from 1995 to 2006 (see appendix 1) and their tendency to outperformed many different asset classes and show low correlations attracted more market players and investors and thus there was a high demand for hedge fund data.

In line with this trend, there's been a need for quantitative models, analyzing hedge funds and provide important information while respecting their privacy profile. The majority of hedge funds are providing their net asset value on a regular basis to commercial data vendors such as TASS, Altvest, Hedge Fund Research (HFR) and Managed Account Reports (MAR). Data vendors do not only collect performance data. For a majority of funds, they record other useful information such as company name, start and ending date, strategies, assets under management, management and incentive fees and manager's name.

Although these databases are subject to a survivorship bias, these net asset values are probably the most reliable source of data publicly available today on the hedge fund industry. Owing to the fact that survivorship bias could significantly affect the quality of the analysis, the HFR database is chosen because it contains an extremely small survivorship bias rate as mentioned before in the literature.

3.1.1 Hedge Fund Dataset

For the construction of the multi factor model, a range of hedge fund indices will be analysed with data extracted from HFR (Hedge Fund Research) along with their relationships with major stock, bond and commodity indices extracted from Bloomberg. The final data consists of monthly observations from January 1998 to August of 2012. Finally, the NAV return of the time series will be converted into logarithmic to simplify the quantitative analysis.

The HFR indices are a series of benchmarks of hedge fund industry performance which are engineered to achieve representative performance of a larger universe of hedge fund strategies. The Computation of an Index net asset value (NAV) uses actual performance of the managed account established for each constituent manager as reported to Hedge Fund Research, Inc. Performance reflects constituent fund management fees, incentive fees, dividends and other distributions and they consist of 6,800 funds that report to the HFR Database. These funds are screened for various reporting characteristics, assets and duration of track record qualities and unique fund strategy inclusion.

The HFRX Global Index is constituted by the aggregation of the single strategy indices as follows (HFR, 2012):

$$NAV_t^{HFRXGL} = \sum_{j=1}^{4} W_j * NAV_t^j$$

where NAV_t^j is the NAV of index j at time t, Wj is the weight of strategy j at time t. The weight of each strategy is set at the time of rebalance and is given by the assets of the strategy in the Hedge Fund Universe as provided by Hedge Fund Research Inc. for the end of the prior quarter (HFR, 2012).

The HFRX Single Strategy Indices correspond to the HFRX Equity Hedge Index, the HFRX Event Driven Index, the HFRX Macro/CTA Index and the HFRX Relative Value Arbitrage Index. These Single Strategy indices are constituted by the aggregation of the eligible sub strategy indices underlying each strategy as follows (HFR, 2012):

$$NAV_t^{HFRXi} = \sum_{j=1}^{n} W_j^i *$$

where $NAV_t^{i,j}$, is the net asset value of the sub-strategy j within strategy i at time t , W_j^i is the weight of substrategy j at time t and i = {Equity Hedge, Event Driven, Macro, Relative Value}.

In particular, the analysis below will use the indices: HFRX: Global Hedge Fund Index, HFRI: Fund of Funds Composite, HFRX: Equity Hedge Index, HFRX: Macro/CTA Index, HFRX: Event Driven Index, HFRI EH: Equity Market Neutral, HFRI ED: Distressed/Restructuring, HFRX ED: Merger Arbitrage Index, HFRI RV: Fixed Income-Convertible arbitrage HFRX Relative Value Arbitrage, HFRI RV: Fixed Income-Corporate Index, HFRI Emerging Markets: Global, HFRI RV: Multi-Strategy Index, HFRI RV: Yield Alternatives Investments, MSCI World Total Index(including the dividend returns), S&P GSCI (formerly the Goldman Sachs Commodity Index), VIX: Volatility Index, S&P Equal Weighting, MSCI Small Cap and the JP Morgan Global Bond Index.

The frequency of the observations for the data is monthly. Therefore on table 4 below, the summary of descriptive statistics of the data are presented such as the monthly mean, standard deviation, variance and skewness.

Table 4

Descriptive statistics of the monthly index returns:

Statistics	Global Hedge Fund Index	Fund of Funds Comp.	Equity Hedge Index,	Macro/CTA Index	Fixed Income-Convertible	Event Driven Index	Equity Market Neutral	Distressed/Restructuring	Merger Arbitrage Index	Volatility Index
Mean	.0043	.0032	.0043	.0049	.0007	.0038	.0032	.0062	.0045	-.0004
Standard Deviation	.0195	.0181	.0251	.0255	.0398	.0199	.0095	.020	.0107	.181
Variance	.0003	.0003	.0006	.0006	.0015	.0003	.0001	.0004	.0001	.033
Kurtosis*	8.170	7.265	6.239	4.016	80.1	8.23	5.02	8.029	6.27	3.73
Skewnes*	-.842	-.882	-.5182	.1911	-7.82	-1.63	-.279	-1.54	-1.18	.5465
Max	.058	.066	.093	.082	.065	.047	.035	.054	.032	.646
Min	-.098	-.078	-.105	-.077	-.42	-.095	-.029	-.089	-.047	-.385

Statistics	Relative Value Arbitrage	Fixed Income-Corp.	Multi-Strategy Index	Emerging Markets Global Index	Yield Alternatives Investments	MSCI World Total Index	S&P GSCI/ Commodities	JP Morgan Global Bond Index	S&P Equal Weight	MSCI Small Cap
Mean	.0033	.0038	.0041	.0044	.0048	.0004	.0077	.0051	.0069	.0060
Standard Deviation	.0218	.0183	.0142	.0406	.0225	.0456	.0703	.0177	.0542	.0565
Variance	.0004	.0003	.0002	.0016	.0005	.0020	.0049	.0003	.0029	.0031
Kurtosis*	20.58	13.77	15.67	25.94	6.472	4.277	5.195	3.394	4.575	4.470
Skewness*	-3.03	-2.32	-2.46	-3.20	-1.16	-.8821	-.759	.0424	-.410	-.629
Max	.066	.044	.038	.109	.065	.096	.191	.064	.187	.163
Min	-.152	-.113	-.088	-.321	-.092	-.18	-.325	-.04	-.2106	-.227

* Denotes significance at the 1% level

3.2 Methodology

The first part of the quantitative analysis in this thesis will try to address the issue of the differences in performance between traditional and non traditional asset classes. In other words, the question which is going to be tackled will be: Do Hedge funds produce superior risk-adjusted returns in comparison to traditional assets? Therefore, the HFR Global Index as well as HFR Strategy indices will be compared with major traditional markets such as equities, bonds and commodities (commonly accepted as the sources of Betas for investors). For the dataset which has been collected, annual data, from 1998 to 2012 have been summed up and calculated to accommodate these comparisons. Firstly, via the net asset values of all these indices, logarithmic monthly and yearly returns have been measured along with annualized volatilities. In this case, the risk metrics which have been used to measure annualized volatility will be the standard deviation of the logarithmic returns and is calculated using the simple formula:

$$\sigma_t = \sigma_{i,j,k\ldots n} * \sqrt{T}$$

The next step is to use the annualized and monthly returns and volatility in order to calculate the yearly Sharp Ratios, as this enables the capture of the risks involved in the investment strategy and presents the level of risk-adjusted returns. This will be the original Sharp's model (1964) which measures the excess return (or risk premium) per unit of deviation in an investment asset or a trading strategy, typically referred to as risk. The Sharp Ratio formula is:

$$(R_p - R_f)/\sigma_p$$

Where:

Rp: Expected portfolio return

Rf: Risk Free Rate (The 12 month US risk free rate (Bloomberg ticker: US0012M) for each year)

σp: Portfolio standard deviation

Sharp ratio is very useful because although a fund could achieve higher returns than the rest of its competitors, it will be a worthwhile investment only if these excess returns weren't achieved under high levels of risk. The greater a portfolio's/funds Sharpe ratio, the better its risk-adjusted performance will be. A negative Sharpe ratio indicates that a risk-less asset/fund would perform better than the particular investment fund. Therefore the sharp ratios will be presented and will be used to compare equities, bonds and commodities along with major hedge fund strategies and a conclusion will be drawn as to whether hedge funds performed better between 1998 and 2012. There will be a key focus on distinguishing the trends between the relatively good and stable period (1998-2007) and the volatile and distressed period (2007-2012) for the financial markets.

The second main objective is to statistically test if different hedge funds strategies achieve statistical significant different mean monthly returns through time by comparing them with each other and with traditional asset classes (equities, bonds, commodities). A paired t-test was applied, for comparison of mean monthly returns between the strategies and the traditional assets. A paired (or "dependent") t-test is used when the observations are not independent of each other. Hedge fund strategies and major traditional asset classes are all driven by interrelated common factors and common underlying financial securities. Consequently, one would expect a relationship between their performances and especially in this case with the particular dataset they could only be considered as dependent on each other. 139 econometric paired t-tests have been conducted in Stata and the p-value was determined as the probability associated with pair T test with a distribution bi-variant. The test essentially is observing at the differences in the values of the two variables and testing if the mean of these differences is equal to zero. The null hypothesis is rejected if the p-value is smaller than or equal to the significance level. The following hypotheses are tested with a significance level of 5%.

Where:

H_0: $\mu_{\Delta t} = 0$

H_α: $\mu_{\Delta t} \neq 0$

Δi (mean difference) = Xi-Yi, where Xi and Yi are the two values of the paired number i, to compare;

i = 1 to 17, where 1: Global Hedge Fund Index, 2: Fund of Funds Composite, 3: Equity Hedge Index, 4: Macro/CTA Index, 5: Fixed Income-Convertible, 6: Event Driven Index, 7: Equity Market Neutral, 8: Distressed/Restructuring, 9: Merger Arbitrage Index, 10: Relative Value Arbitrage, 11: Fixed Income-Corporate Index, 12: Multi-Strategy Index, 13: Emerging Markets Global Index, 14: Yield Alternatives Investments, 15: MSCI World Total Index, 16: S&P GSCI (formerly the Goldman Sachs Commodity Index), 17: JP Morgan Global Bond Index.

This T-test was applied in the comparison of the 17 different strategies. The t-statistic for a paired sample test is computed as follows:

$$t = \sum d \Big/ \sqrt{\frac{n(\sum d^2) - (\sum d)^2}{n-1}}$$

Where d is the mean difference between two samples, s² is the sample variance, n is the sample size and t is a paired sample t-test with n-1 degrees of freedom. At this stage it will be also very interesting to observe the correlation between traditional asset classes and non traditional asset classes as well as the correlation between the major hedge fund strategies to arrive at some viable conclusions.

In the final part of the quantitative analysis, a multi factor model will be constructed which relies essentially on an extension of Sharpe's (1992) return-based style analysis technique (style regression) for mutual funds and portfolios with the main difference being that the risk-free rate is deducted and the Hedge fund return Index is used as the dependent variable. This extension is favourable as it takes into account special characteristics of hedge funds such as the ability to engage in complex short and high leveraged positions.

As mentioned earlier, the analysis employs a time series of net asset values which have been converted into returns with a logarithmic return formula on a monthly base from 1998 to 2012. Suppose that NAV_t is the net asset value of a hedge fund at time t. From the fund's net asset values, returns are derived as follows:

$$R_t = LN\left(\frac{NAVt}{NAV_{t-1}}\right)$$

Multiple asset class factor models are structured to explain and model excess returns of hedge funds and distinguish the alpha and beta in them. Therefore, more asset class factors are added for each regression analysis representing traditional asset classes (stocks, bonds, commodities). The main traditional asset class factors which shall be used in the multifactor models are the monthly logarithmic returns of the MSCI World Total Return Index (Includes dividends distributions), the S&P Commodities Index and the JP Morgan Bond Index. Subsequently, the additional factors would be the SPX Volatility Index, the S&P Equal Weighting Index Return (includes dividends distributions) and the MSCI Small Capitalization Total Return Index (includes dividends distributions). The reason behind adding the equal weighting and small capitalization index could be explained based on the behaviour of hedge funds with regards to the equity selection within their Strategies. The main MSCI World Index or the S&P 500 provides the total returns based on the capitalization/size weighting of the companies within the indices and sometimes is not able to capture these complex characteristics in hedge fund equity portfolios for the construction of their strategies. Hedge fund managers are not benchmarked to any index thus they consider stocks equally without any market capitalization bias. An Equal Weighting and a Small Capitalization Index could be a better reflection of the opportunity set and the beta available. Therefore by adding these extra variables in the multi factor models, it will provide better insights and indicators about the excess returns of Hedge Funds and their behaviour as it will be able to capture their complex unbiased selection standards within the screening process.

The multi-factor model below is suggested to explain the time-series of returns.

$$Rt = \alpha + \sum_{k=1}^{N} \beta k \; Fk\mathrm{t} + \varepsilon t$$

Where Fk_t is the value of factor number k at time t, α is the alpha returns, β is the beta of the factor. The intercept term of the model (alpha) could be interpreted as the portion of return unexplained by the factor model and it could provide insights about the nature of hedge fund returns and the differences between them and the systematic market returns of traditional asset classes.

Therefore the main regression models would be:

$$R(Hedge\ Fund) = \alpha lpha + \beta 1 * (MSCI\ Equities) + \beta 2 * (S\&P\ Commodities) + \beta 3 * (JP\ Morgan\ Bond) + \varepsilon t$$

$$R(Hedge\ Fund) = \alpha lpha + \beta 1 * (MSCI\ Equities) + \beta 2 * (S\&P\ Commodities) + \beta 3 * (JP\ Morgan\ Bond) + \beta 4 * (VIX) + \beta 5 * (S\&P\ Equal\ Weighting) + \beta 6 * (MSCI\ Small\ Cap) + \varepsilon t$$

On the second main model, more traditional asset factors were added to observe the capitalisation bias of hedge fund managers. More multifactor models will be regressed to interpret different major hedge fund strategies returns with traditional asset classes. The regression models will be developed in Stata with, using particular software commands and functions (See appendix 5).

Firstly, the alpha and the beta returns will be distinguished and then in order to test the statistical significance of the multi-factor return model's regression coefficients, the standard t-test statistic shall be used – it is calculated as follows (Hill et al, 2011):

$$\frac{\mathrm{\beta i}}{\mathrm{s.e.\,(\beta i)}} \sim \mathrm{tn} - \mathrm{k}$$

where βi is the estimated coefficient and s.e. stands for the standard error. Under the null hypothesis that the coefficient is equal to zero, the test statistic is t distributed with (n - k) degrees of freedom; n denotes the sample size and k denotes the number of estimated coefficients (including the intercept). Furthermore, the R^2 is computed to assess the overall model fit as follows (Hill et al, 2011):

$$R^2 = SSR/SST$$

where SSR is the sum of squared deviation of observations due to the regression and SST is the total sum of the squared deviation. Additionally, an F-test is conducted with the null hypothesis (H0); i.e. regression coefficients are equal to zero (Hill et al, 2011).

Let n be the number of observations, k be the number of coefficients (including the intercept) and SSE be the sum of squares due to the error, then the F-statistic is computed as follows (Hill et al, 2011):

$$\frac{\frac{SSR}{K-1}}{\frac{SSE}{n-k}} \sim F_{k-1,(n-k)}$$

However, there are numerous problems applying style analysis to hedge fund returns. With Hedge funds, the appropriate market indices to include as explanatory variables are not obvious. Secondly, hedge funds as mentioned before undertake dynamic trading strategies which switch asset exposures rapidly and this invalidates the standard regression model. Stationary traditional buy and hold portfolios such as equity and bond indices do not capture the dynamic asset allocation and the derivatives usage of hedge fund managers. However, the application of time series data in the analysis will possibly result in less problematic regression models. Finally, it’s argued that the factor replication approach does not take into account the non-linear payoffs of hedge funds and it adjusts to changes in hedge fund exposures with a significant time lag.

4 Empirical results

4.1.1 Do Hedge funds produce superior risk-adjusted returns in comparison to traditional assets?

The outlined results must be observed with these peculiar caveats; the period between August 2007 and December 2008 can be identified as an anomaly in the sequence to the sub-prime crises in the USA. Table 5, 6 and 7 present the returns, the volatility and the risk adjusted performance using the sharp ratio of major hedge fund indices and traditional asset indices. In particular, for the period of 1998 to 2011, most of the main hedge fund strategies performed much better than the traditional asset classes and with a much lower volatility. Hedge funds produced superior returns in comparison to equities with much less volatility. Commodities achieved the highest returns but with enormous volatility thus the sharp ratios are lower than those of the hedge fund strategies. Merger Arbitrage strategies seem to achieve the best risk adjusted return along with distressed/restricting strategies – this could be perhaps attributed to the credit crisis of 2007-2008. The only traditional asset class which performed very well and produced excellent risk adjusted returns was the Bond market. This could be perhaps attributed to the volatile period of 2008 which saw much flight to quality as investors sought to put their capital in safe haven corporate and government bonds as these were less volatile than other traditional and non-traditional asset classes.

Table 5: Over 1998-2011 period

Investment Asset Classes	Return	Volatility	Sharp Ratio
Global Hedge Fund Index	5.41%	6.83%	0.27
S&P 500	1.40%	17.38%	-0.13
JPM Global Bond Index	6.33%	6.22%	0.44
MSCI	0.14%	15.86%	-0.22
Commodities	9.95%	24.38%	0.26
Equity hedge Index	5.58%	8.84%	0.23
Hedge funds of funds composite	4.16%	6.33%	0.09
Macro funds / CTA Index	6.34%	8.94%	0.31
Event driven Index	4.88%	6.99%	0.19
Merger Arbitrage Index	5.78%	3.76%	1.54
Distressed/restructuring Index	7.68%	7.00%	0.58
Emerging markets Global Index	5.63%	14.22%	0.14
Alternative Investment Yield index	5.81%	7.71%	0.29
Fixed Income Corporate Index	4.54%	6.40%	0.15

At this juncture, in order to observe in-depth while bearing in mind certain caveats with respect to the performance results and determine if hedge funds produce superior adjusted returns over time, it will be interesting and prudent to separate the periods of the dataset into the steady period between 1998 and 2007 and the distressed or volatile period of 2007 - 2012. Of course, there was volatility and distress in the financial markets in the lead up to 2007 caused by events such as the dot.com boom and the collapse of LTCM. However, hedge funds performance remained uncorrelated, steady and less exposed in comparison to the performance of traditional asset classes from 1998 to mid 2004 (see appendix 4).

Table 6: 1998-Mid 2007

Investment Asset Classes	Return	Volatility	Sharp Ratio
Global Hedge Fund Index	9.91%	5.82%	1.09
SPX	5.11%	14.62%	0.10
JPM Global Bond Index	5.88%	5.82%	0.39
MSCI	3.83%	14.21%	0.02
Commodities	11.32%	21.89%	0.35
Equity hedge Index	11.54%	7.58%	1.05
Hedge funds of funds composite	7.07%	5.85%	0.60
Macro funds / CTA Index	9.95%	8.65%	0.74
Event driven Index	8.70%	6.34%	0.81
Merger Arbitrage Index	6.91%	3.78%	0.88
Distressed/restructuring Index	10.93%	5.78%	1.27
Emerging markets Global Index	7.60%	15.13%	0.27
Alternative Investment Yield index	7.99%	6.66%	0.66
Fixed Income-Corporate Index	6.01%	4.57%	0.53

As can be observed in table 6 above, the global hedge fund index achieved the most superior risk adjusted returns along with the equity hedge and distressed/restructuring index when compared to any of the traditional asset classes. For the particular period, i.e. 1998 to mid-2007, it’s interesting to observe the difference in the bond market performance in relation to the previous table (6), which captured the whole period of 1998-2011. Until 2007, the bond market did not perform better than hedge funds because there wasn’t any debt crisis and ‘flight to quality’ of investor’s capital as evidenced by the direction of investments after 2007. As table 7 shows, hedge funds did not perform well between 2007 and 2012 due to the subprime crisis and the Euro debt crisis. Nonetheless, their volatility was much smaller than equities, bonds and commodities. In addition, particular hedge fund strategies such as merger arbitrage, fixed income-corporate yields, emerging markets and alternative investments and distress/restricting performed much better than traditional asset classes. The main hedge fund strategies which did not performed well were macro and equity hedge. This could be attributed to the massive liquidation and the distress in the financial markets which was triggered by the events of Lehman Brothers and the subprime market collapse.

The aforementioned strategies are more exposed and tied to macroeconomic factors and traditional financial securities and as such were heavily affected.

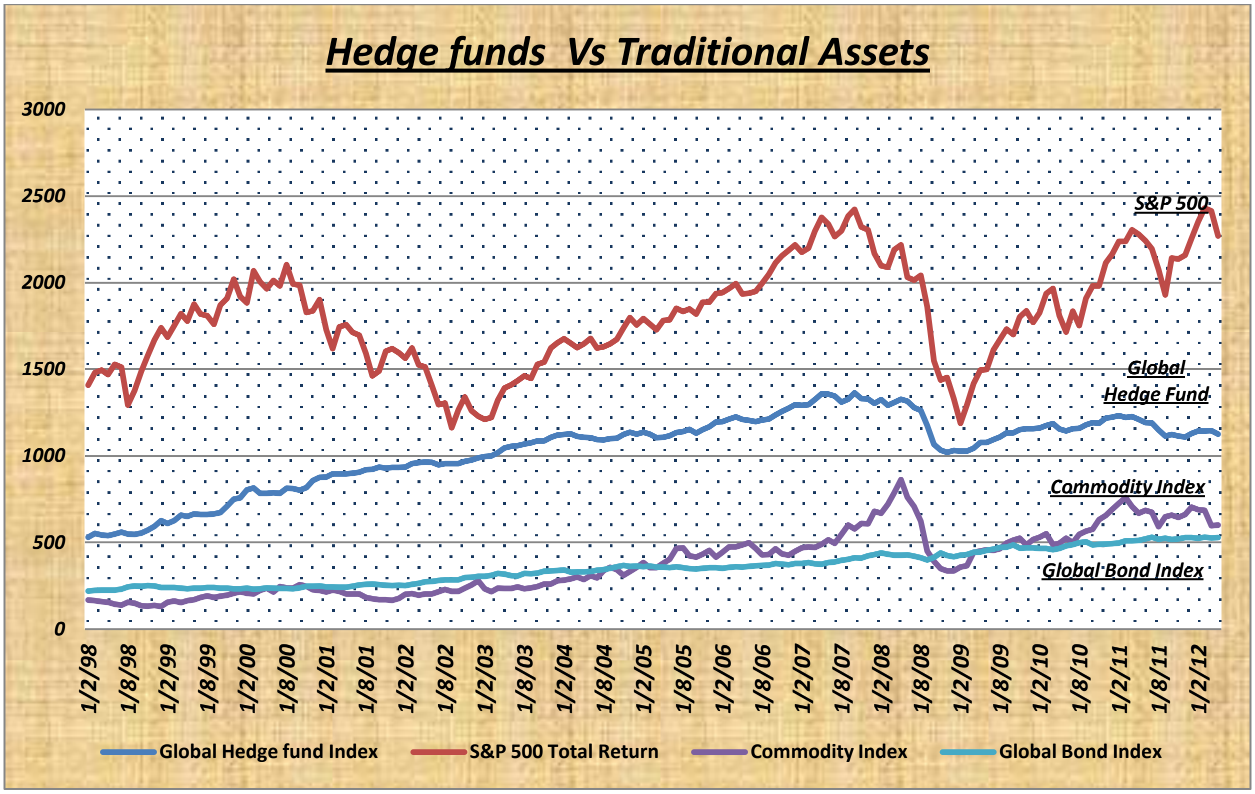
Table 7: Mid of 2007- Mid of 2012

Investment Asset Classes	Return	Volatility	Sharp Ratio
Global Hedge Fund Index	-3.74%	4.26%	-1.72
SPX	-4.72%	21.45%	-0.39
JPM Global Bond Index	-13.17%	45.10%	-0.37
MSCI	-5.68%	18.46%	-0.50
Commodities	-15.56%	52.49%	-0.36
Equity hedge Index	-6.42%	9.74%	-1.03
Hedge funds of funds composite	-1.89%	6.70%	-0.82
Macro funds / CTA Index	-2.23%	8.68%	-0.67
Event driven Index	-2.87%	7.46%	-0.87
Merger Arbitrage Index	3.00%	3.53%	-0.17
Distressed/restructuring Index	1.20%	8.47%	-0.28
Emerging markets Global Index	0.67%	12.12%	-0.24
Alternative Investment Yield index	1.70%	9.53%	-0.20
Fixed Income-Corporate Index	1.98%	8.70%	-0.18

The observable trend on graph 1[8] below provides an illustration of how the global hedge fund index performed in comparison to the main traditional indices (S&P 500, Bond Index and Commodities index) from 2008 to 2011, i.e. using the net asset values of these asset classes. The Hedge Fund Index shows a steady upward movement through the years without significant volatility in comparison to the Equities and Commodities indices which exhibit massive volatile trends over time. The bond market performed better without much volatility in a very steady motion but with less returns than Hedge funds.

[8] The graph was created manually on an excel spreadsheet with the detailed monthly HFR Data.

Graph1



Source: HFR Database

The general conclusion after the performance measurement conducted and presented above is that hedge funds produce superior risk-adjusted returns over time in comparison to traditional assets. Also, they carried fewer risks when volatilities are compared. Our results are consistent with numerous academic results and literature findings. Particular hedge fund strategies are performing well with significantly less volatility in both prosperous and distressed times. Sub-strategies which are more tied to macroeconomic factors and traditional financial securities such as Macro, Emerging Markets and Equity Neutral appear to be exposed and influenced negatively in periods of loss of investors' confidence and volatility in the markets. However, the standard deviation of the return measure as a total risk metric might not be able to fully capture the complex risk taking from hedge fund's dynamic and highly leveraged strategies. Additionally, the analysed time period of 1998 to 2012 covers a complete macroeconomic cycle and some events which occurred over this period exposed some unique hedge fund risks. The substantial losses incurred by several hedge funds as a result of the global crises of 2008 demonstrate the impact of these extreme events. The most dramatic negative returns have occurred in highly leveraged global hedge fund categories which engaged in rapid liquidation in the month of August in 2007 in order to raise capital. Owing to this turn of events, one should be cautious when analysing them by distinguishing between the time periods and their peculiar events while also taking into consideration the inherent biases in hedge fund data and the nature of strategies in order to arrive at certain conclusions and justify the above results.

4.1.2 Do hedge funds strategies achieve statistical significant different mean monthly returns through time?

According to the statistical results of the 139 paired t-tests (see appendix 6), the null hypothesis of equal mean monthly returns cannot be rejected between the strategy Distressed/Restructuring and Fund of Funds, Fixed Income-Convertible, Event Driven Index, Equity Market Neutral and the global hedge fund with Relative Value Arbitrage, Fixed Income-Corporate Index and Multi-Strategy Index. The p-value[9] for Funds of Funds and Distressed/Restructuring presents the lowest value at 0.0017. For Fixed Income-Convertible and Distressed/Restructuring the p-value is 0.0180; Distressed/Restructuring and Event Driven presents a p-value of 0.0094; for Equity Market Neutral and Distressed/Restructuring, the p-value is 0.026; for Distressed/Restructuring and Relative Value Arbitrage, the p-value presented is 0.0116; for Distressed/Restructuring and Fixed Income Corporate, the p-value presented is 0.0039 and finally for Distressed/Restructuring and Multi-strategy, the p-value is 0.0262. For all the other strategies, as illustrated by appendix 6, it is possible to reject the null hypothesis. The mean of the monthly returns of most combinations between strategies and traditional asset classes are coherent individually and between themselves as well and the mean difference of these combinations are not different from zero. The pair sample correlations in appendix 7 supports and provide(s) additional insights on the conclusion of a consistent overall coherence between the strategies. By observing the significant values of correlation between those same strategies; the correlation between Funds of Funds and Distressed/Restructuring is 0.8331; the correlation between Fixed Income-Convertible and Distressed/Restructuring is 0.6212; the correlation between Distressed/Restructuring and Event Driven is 0.8351 and so on (see appendix 6 for more details). The majority of them display positive and significant values. Some of them are closer to zero but they are all strong positive correlations. Other interesting correlations appeared when looking at the correlation values between hedge fund strategies and traditional asset classes. Equities, implied volatility and commodities versus different hedge fund strategies present coefficients very close to 0 while bonds versus hedge fund strategies are negatively correlated over time.

A general conclusion when analysing the statistic results could be that, the seventeen strategies are somehow coherent amongst themselves and the purity of these strategies is not significant. Thus, the mean of the monthly returns of the strategies are statistically coherent between themselves.

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[9] See the highlighted numbers with red colour at the Appendix 6.

4.1.2.1 What is the driver of hedge fund returns: alpha, beta (systematic market exposure) or other factors? How can alpha and beta interact? Is the market beta a constant or is it a variable and how has it evolved over time?

As mentioned in the methodology, in order to observe the key drivers of hedge fund returns, a multi-factor return model was constructed by regressing hedge fund monthly returns with the monthly returns of traditional asset classes. The results will enable us to distinguish between alpha and systematic exposure (beta) returns and identify how much exposure hedge fund returns have to equities, bonds and commodities. By applying econometric analysis in Stata， the main multi-factor model appears to be:

$$R(Hedge\ Fund) = 0.0041 + 0.2645 * (MSCI\ Equities) + 0.0014 * (S\&P\ Commodities\ ) + 0.0237 * (JP\ Morgan\ Bond) + \varepsilon$$

The hedge fund return factor model distinguishes the driver of returns by producing a constant which is considered as the individual alpha return and the market beta return – these are obtained from each traditional asset class and are all monthly returns. It is expected to confirm that pure hedge funds should have a limited exposure to the equity, bond and commodity markets and create significant alpha returns over time. The alpha returns are 0.41% per month which is equivalent to 4.92 % annually. Holding all other factors constant, a 1% monthly increase in the MSCI returns increases hedge fund returns by 0.26%. The resulting T-statistic and p-values indicate significance at the 1% level for the MSCI Index returns while the Bond and the Commodity indices are statistically insignificant. The constant in the regression equation which is the 'alpha' term is also significant. Given that the constant return is statistically significant and independent of beta, it provides evidence that Hedge Funds produce 'alpha' in comparison to benchmark indices of systematic exposures i.e. equities, bonds and commodities. The R-squared statistic suggests that 37% of the variations in hedge fund returns are explained by the explanatory variables. This shows that the returns of traditional assets have very limited effect however there is also significant variation from these betas which eventually drive the alpha returns. Thus, the drivers of hedge fund returns in the multi-factor model show that there is very limited relevance with traditional assets and their systematic market exposure (beta) interacts slightly with their Alpha.

Subsequently, another multi-factor model was employed which included more traditional asset classes. As fund managers are not benchmarked to any index and as such consider stocks equally without any market capitalization bias, an Equal Weighting and a Small Capitalization Index monthly returns was added.

$$R(Hedge\ Fund) = 0.0037 + 0.202 * (MSCI\ Equities) + 0.0134 * (S\&P\ Commodities) + 0.0075 * (JP\ Morgan\ Bond) + 0.0164 * (VIX) - 0.1603 * (S\&P\ Equal\ Weighting) + 0.256 * (MSCI\ Small\ Cap) + \varepsilon t$$

By adding the rest of the traditional asset classes, the model shows that all the equity variables are statistical significant. The betas of S&P Equal Weighting Index and MSCI Small Cap Index are highly significant and demonstrate that hedge fund managers are not biased with respect to equity capitalization. The betas on commodities and bonds are insignificant and the yearly Alpha return estimated to be 4.44% is statistically significant as well. Holding all other factors constant, a 1% monthly increase in the MSCI Small Cap returns increases hedge fund returns by 0.25%. R-squared suggests that 49% of the variations in hedge fund returns are explained by the explanatory variables. The model was improved because more equity variables were added.

It is interesting to note that the only significant traditional market index with a statistical significant relationship was the Equities Index. A large proportion of hedge funds employ strategies which involve investing in Equities and complex derivatives which are tied with Equities. Even if some strategies are constructed in a way that they are not exposed to systematic market factors, they still involve trading algorithms which long and short equities around the globe and make usage of equity derivatives. As a result of this, traditional asset classes can be a leading indicator of investors risk appetite which might justify the relationship and its significance.

4.1.2.2 How different Hedge Fund Strategies affected by traditional market factors?

The creation of multi-factor models which attempt to explain hedge fund returns of particular main sub-strategies provide results (see appendix 8) which support our main hypothesis and the literature.

Macro/CTA Index: by regressing returns with equities, commodities, bonds and implied volatility, only equities and commodities are significant while only 15% of the variations in Macro/CTA returns are explained by the explanatory variables with a significant alpha of 6% yearly. A 1% increase in the MSCI returns increases Macro/CTA returns by 0.12% monthly or 1.44% yearly while a 1% increase in S&P Commodity returns decreases Macro/CTA returns by 0.06 yearly. The F-statistic is less than 5 thus there is no joint significance. These results conclude that the particular hedge fund strategy does not really interact with systematic market exposures and it produces high alpha returns uncorrelated with traditional asset betas. This could be attributed to the nature of the particular sub-strategy. This strategy employs an opportunistic and speculative top-down approach in order to take advantage of market movements through long and short positions in the world's major capital or derivative markets with portfolios of stocks, bonds, currencies, commodities and derivatives instruments in developed and emerging markets. The strategy relies on the ability to make superior forecasts compared to other market participants and act quickly and decisively. As a result, the returns on this strategy should be expected to be irrelevant with systematic exposures of traditional asset returns because of the usage of leverage, short positions and complex derivatives.

Equity Hedge Index: by regressing its returns with traditional equity factors, there is statistical significance with the explanatory variables; however, only 57% of the variations in Equity Hedge Index returns could be explained by the variables while there is a strong significant alpha of 4.8% yearly. As this strategy seeks to take advantage of undervalued and overvalued securities by engaging in long and short positions in the market, the statistical significance with the equity factors is justified. In fact, it could be observed that the betas to risk factor are higher and the t-stat is also higher.

Equity Market Neutral: by regressing its returns with equity factors, the MSCI is statistically insignificant while the Equal Weighting and Small Cap Index are significant. Only 17% of the variation in Equity Market Neutral returns could be explained by the explanatory variables while there is a significant alpha of 3.6% annually. It is completely justified because by employing this strategy, the funds attempt to generate alpha returns while eliminating systematic risk and keeping beta neutral. In fact, it could be observed that the beta to risk factor is much lower and the t-stat is also lower.

Emerging Markets Index: by regressing its returns with traditional asset classes, only the MSCI is highly significant with a strong significant alpha of 5.28% annually and with an R-squared of 60%. A 1% rise in the MSCI returns increases emerging markets index returns by 0.50% monthly or 6% yearly

By regressing the Event Driven Index, Distressed/Restructuring Index, Merger Arbitrage Index, Fixed Income-Convertible arbitrage Index, Relative Value Arbitrage Index, Fixed Income-Corporate Index and Multi-Strategy Index returns, the results are very similar. Appendix 8 depicts the results obtained from the multi-factor model of the analysis. The results reported are particularly strong. Every strategy created significant alpha at the 5% significance level. The results obtained using sub-strategy indices indicate low market betas on an absolute term but are significantly positive. In the majority of cases, market factors are significantly positive but they do not explain a major part of the alphas. With respect to exposures, almost all strategies are significantly exposed to the equity market. Few strategies are significantly exposed to other factors. There is also high exposure to Equal Weighted and Small Cap indices. Thus, hedge funds profit from the over-performance of small companies over the period under analysis by being small cap biased. With regards to bonds, the JP Morgan Bond Index factor is significantly negative for some strategies but no single strategy is significantly exposed to this factor indicating an inverse yet insignificant relationship between hedge fund returns and the bond market.

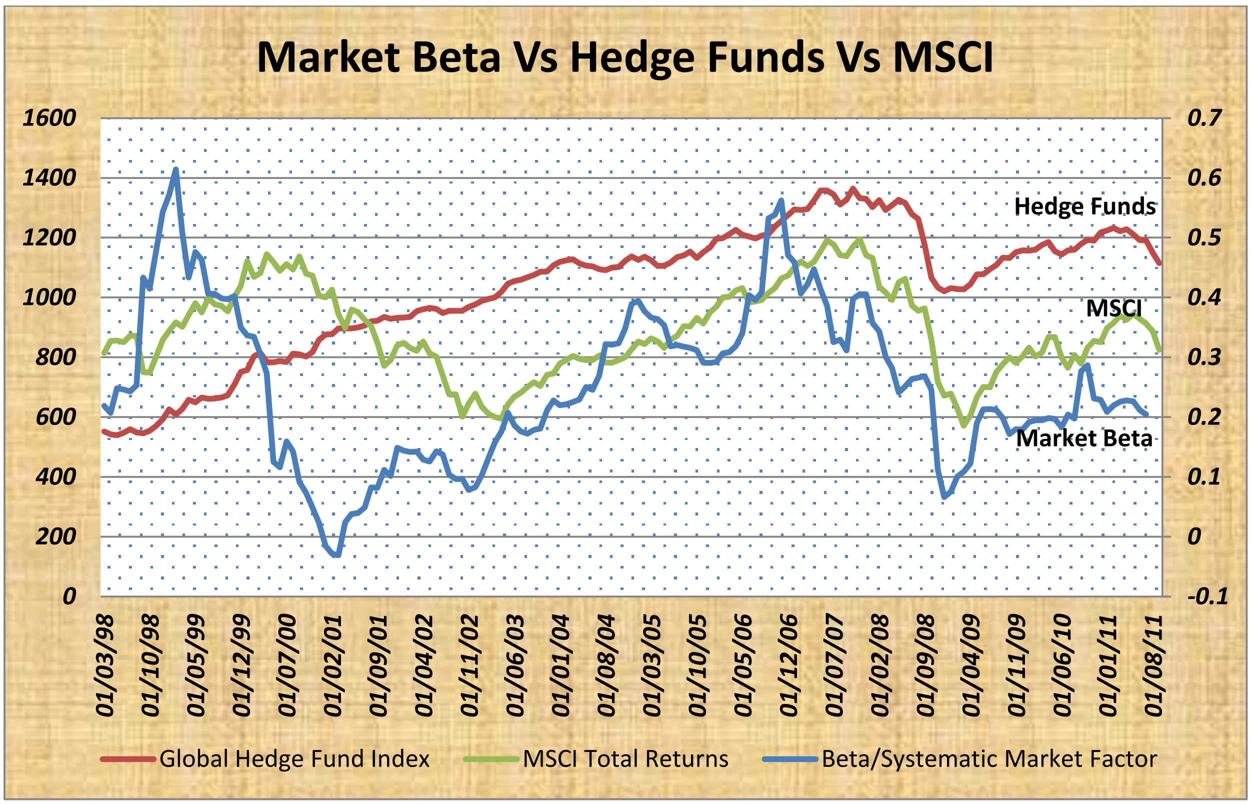
Only 25 - 58% of the variation of all these strategy returns could be explained by the explanatory variables. Whiles they all produce strong statistical significant alphas, only the equity asset classes' returns are significant explanatory variables. It's very interesting to observe that while the equity variables are statistical significant with the fixed income and distressed strategies, the bond variable is not. This could be attributed to the speculative nature behind fixed income arbitrage and the distressed/restructuring strategies employment of complex usage of derivatives and very rapid long and short trading in bonds and equities. The JP Morgan Index probably captures the long run and steady performance of corporate bonds based on their yields and their default probabilities. However, it doesn't capture complex speculative distressed situations and bond arbitrage strategies which hedge funds employ with the usage of derivatives and leverage. Thus based on the statistical results and the levels of the fitness of the models (R-squared), it could be concluded that Hedge fund returns cannot be explained by traditional asset classes. Neither the returns of commodities, bonds and equities can fully capture and explain the complex structure of hedge fund strategies. However, there is some correlation and dependence on systematic market factors (beta) - mainly with equities. This demonstrates that hedge funds do not create pure alpha as there is always a slight reliance on market betas, however, it's always limited. Of course with the benefit of hindsight, it could be argued that over the years, there have been some famous examples where particular hedge funds made very successful trades and created pure alpha (see Paulson and Soros case) as the bets were dependent on particular systematic factors and market betas. Of course there is a need for further research and analysis into particular sub-strategies using more data and more factors but the limited availability of hedge fund data makes this quite evasive.

4.1.2.3 Is the market beta a constant or is it variable and how has it evolved over time?

Whilst the main regressions over the period show a statically significant coefficient to MSCI equities return, it would be useful to look into the market beta coefficient and observe how it varies over time in order to support the initial argument that hedge fund returns are non-correlated and irrelevant with respect to traditional asset classes. Graph 2 below is a plot of the Beta returns/systematic market factors between the MSCI and the Global Hedge Fund Index along with a comparison with the actual MSCI and Hedge Fund Returns. By observing the Graph, it could be noted that beta is variable over time and hedge fund returns are uncorrelated.

Hedge funds unlike traditional funds have the flexibility to decide on the level of risk and how much to invest in certain markets. Whilst the quantitative analysis proves that an element of the hedge fund returns could be related[10] to 'market beta' (mainly equities) it is also comprehensible that it's not constant. Market beta varies over time and hedge funds are able to decide whether to allocate capital to a traditional factor or not. Although statistically part of their returns could be identified as beta, one could argue that the allocation decision lies on the chase of 'alpha' returns and it's not just a passive bet. In other words, due to the speculative nature of hedge funds and the employment of complex investment strategies within their investments, they are always chasing alpha and the main focus is always to outperform systematic market factors (beta) by producing abnormal returns. They are not focused on achieving just a decent performance as traditional asset classes but on outperforming them by creating abnormal returns.

Graph 2



Source: HFR, Bloomberg

Based on the graph above, it's apparent that over the 13-year period, hedge funds outperformed the systematic market beta of the equity market with much less spikes on their performance. Clearly, there is a grey area and the simple classification of beta and alpha for hedge funds is not definitive. One could argue that hedge returns are driven by alpha, traditional market beta, timing skill and many other factors.

10 Note that this relation is significant but limited considering the R squared of the regression models.

5 Conclusion

This extensive financial study provides insights on hedge funds by analysing the persistence in hedge fund returns and their differences with traditional asset classes, the complex strategies employed, the key factors behind the returns and the distinction between alpha and beta. The analysis employs metrics such as the Sharpe score, alpha and beta. With hindsight, based on the private nature of hedge funds and the limited public information about their investment strategies, there are still many grey areas with respect to the methodology and the details behind these complex profitable strategies which they employ. As the primary aim of hedge funds is to outperform the financial markets (seeking alpha), there is always a sense of 'hiding the recipe to a great sauce' thereby creating extra asymmetries of information. Hedge funds via their modus operandi are always trying to capture inefficiencies in the markets and achieve abnormal returns. The general perception is that, the disclosure of one's strategies creates transparency and by so doing reduces market inefficiencies which in turn limit the production or pursuit of alpha, i.e. excess and persistent return.

The data for the thesis is made up of a complete market cycle, i.e. it entails both bear and bull market conditions from 1998 to 2012. By historically assessing the performance of hedge funds, it could be demonstrated that hedge funds produce superior risk-adjusted returns over time in comparison to traditional assets and carry fewer risks when volatilities are assessed. By comparing main hedge fund strategies to each other and with some traditional asset classes, it could be suggested that some strategies should be studied more deeply considering the fact that the null hypothesis of equal mean of monthly returns can be rejected. However, the correlation between many of these strategies is high, reinforcing the aforementioned suggestion. Therefore, the concluding remarks may suggest that the purity in each studied style is not as developed and accurate as we may suppose. Also it's suggested that hedge fund strategies returns have mainly very low correlations with traditional asset classes returns. However, it's important to note that the aftermath of the quant crisis in 2007 was a turning point as it appears that there is an upward trend of higher correlations between hedge fund returns and traditional asset classes. The correlation picked up in 2007 because of the systematic and long lasting nature of the market's decline. Perhaps, this could be attributed to the constant market volatility over the last 5 years, lack of investor confidence, absence of risk appetite and liquidity constraints. Typically, hedge funds possess assets-carrying risk and seek bets. Therefore, in a distressed and turbulent market environment, there is a decline across all different asset classes within the investment management industry hence correlations between these assets tend to rise.

In this analysis, it could also be concluded that hedge funds possess the ability to create positive alpha consistently and systematically with limited volatility whilst outperforming traditional asset classes. The beta exposure appears to be the most effective way of classifying hedge funds in order to detect persistency and correlations in the returns. Also, systematic market factors or 'market beta' appears to be variable with limited correlation, reliance and exposure to hedge fund returns. However, this is a variable beta that managers may try to time and capture using their prediction models. These results hold not only for a full market cycle but also when separating bull and bear market conditions. This analysis is of particular interest because it clearly proves that some funds consistently and significantly outperform classical markets. Therefore, hedge fund returns persist over time. However, even if this proves attractive to investors, it should be evaluated with caution because it is not easy to profit from. Hedge funds are classified usually as illiquid investments even if they tend to become more liquid via exchange investment fund units and secondary market transactions. It takes time for investors to close a position and most hedge funds have lockup period stipulations.

As mentioned earlier, some of the most successful Hedge Fund Houses have achieved abnormal returns at specific periods. The evidence on persistence is strong for winners but it could be also strong for losers from time to time by comparing individual funds to each other. The fact that individuals such as George Soros, John Paulson, Ken Griffin, Cliff Asness, Ed Thorp, Jim Simons and Peter Muller have achieved massive gains from speculative bets and trades does validate such trends - one should not consider this as the rule of thumb. As wisely noted by Nassim Nicholas Taleb (2004), an iconoclast with respect to quant models and hedge funds: If one puts an infinite number of monkeys in front of (strongly built) typewriters and lets them clap away, there is a certainty that one of them will come out with an *exact version of the 'Iliad,' Now that we have found* that hero among monkeys, would any reader invest *his life's savings on a bet that the monkey would write the 'Odyssey' next?*

The prevailing academic literature suggests that hedge funds were not the cause of the Asian crisis or other major world economic collapses. The financial markets react quickly to information. As a result, when countries or firms have weak economic fundamentals and fail to meet their obligations, funds flee and the market reacts quickly. While such rapid capital flight may have its own associated problems, the alternative to free flows is almost always worse. If investors were unable to retrieve their invested capital, they would most likely never invest. The evidence indicates that hedge funds do not solely cause market turmoil. Rather, the evidence suggests that the highly leveraged trades and the rapid liquidity withdrawals employed by hedge funds could lead to market disruptions when they are subsequently unwounded. The unwinding of the leveraged 'carry trades' led to the 1994 Mexican Peso Crisis, the 1992 ERM Crisis and the 1997 Asian Currency Crisis in which hedge funds played a significant role but were not the key instigators. 2008 saw the biggest financial turmoil in the markets since the 1930s, especially during the August 2007 ‘Quant Crisis’. In only a few days, a number of quantitative long-short equity funds experienced unprecedented losses in seemingly ‘normal’ market conditions. Quant strategies such as targeted hedging as well as quantitative risk controls were highly instrumental in maximizing leverage. There was also a huge amount of crowding in many quant strategies and many quant funds engaged in very similar strategies often involving carry trades around the globe, going long on value stocks and shorting growth stocks. When the deleveraging hit in August 2007, those crowded strategies blew up in a spectacular fashion. Fat tail moves risk models, highly sophisticated measures of volatility had been spiking and therefore positions based on carry trade where collapsing. A collapse in the subprime market triggered margin calls in hedge funds forcing them to unwind positions in equities which in turn led to a contagion and other hedge fund were forced into unwinding positions in everything, from currencies to future markets to options around the world as the carry trade unravelled.

However, with the benefit of hindsight, the financial meltdown which took place in 2007 could be attributed mainly to a mixture of deregulation, low interest rates and the flood of liquidity fuelled speculative excess the likes of which markets had never seen. The result was a global economic bubble across all asset classes further fuelled by massive leverage and a maze of complex derivatives. The Lehman collapse shuttered assumptions built over decades; that modern finance eliminates risk, asset prices would always appreciate and that markets operate perfectly and efficiently when free. The 1929 lessons had been ignored by successive governments over the past 25 years and the event has been repeated when many didn’t expect it (Logothetis, 2011). The global economy show two decades of globalization, deregulation and misplaced confidence.

In a speech at the National Conference on the Securities industry, Timothy Geithner (2004), the current US Secretary of the Treasury highlighted the continuous importance and the systematic risk hedge funds pose to the entire financial system. It is true that these investment vehicles serve an important purpose yet it would be naïve to ignore the implications of their activities to the financial system and the broader economy thus a future area of concern for regulatory bodies and government agencies could be geared towards improving transparency within the hedge fund industry and by so doing reducing information inefficiencies. Elsewhere, future academic research could be directed towards dynamic investment models and the fundamental nature of the complex strategies employed by these alternative investment vehicles.

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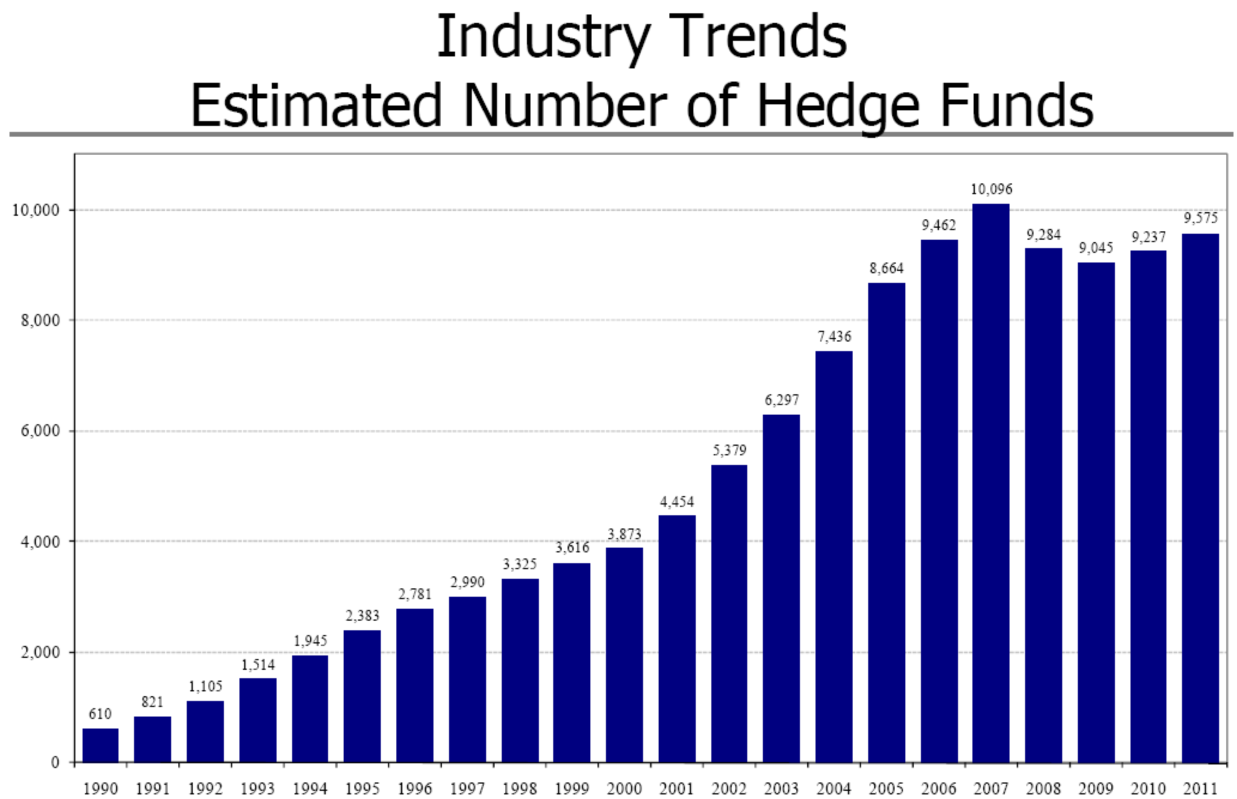
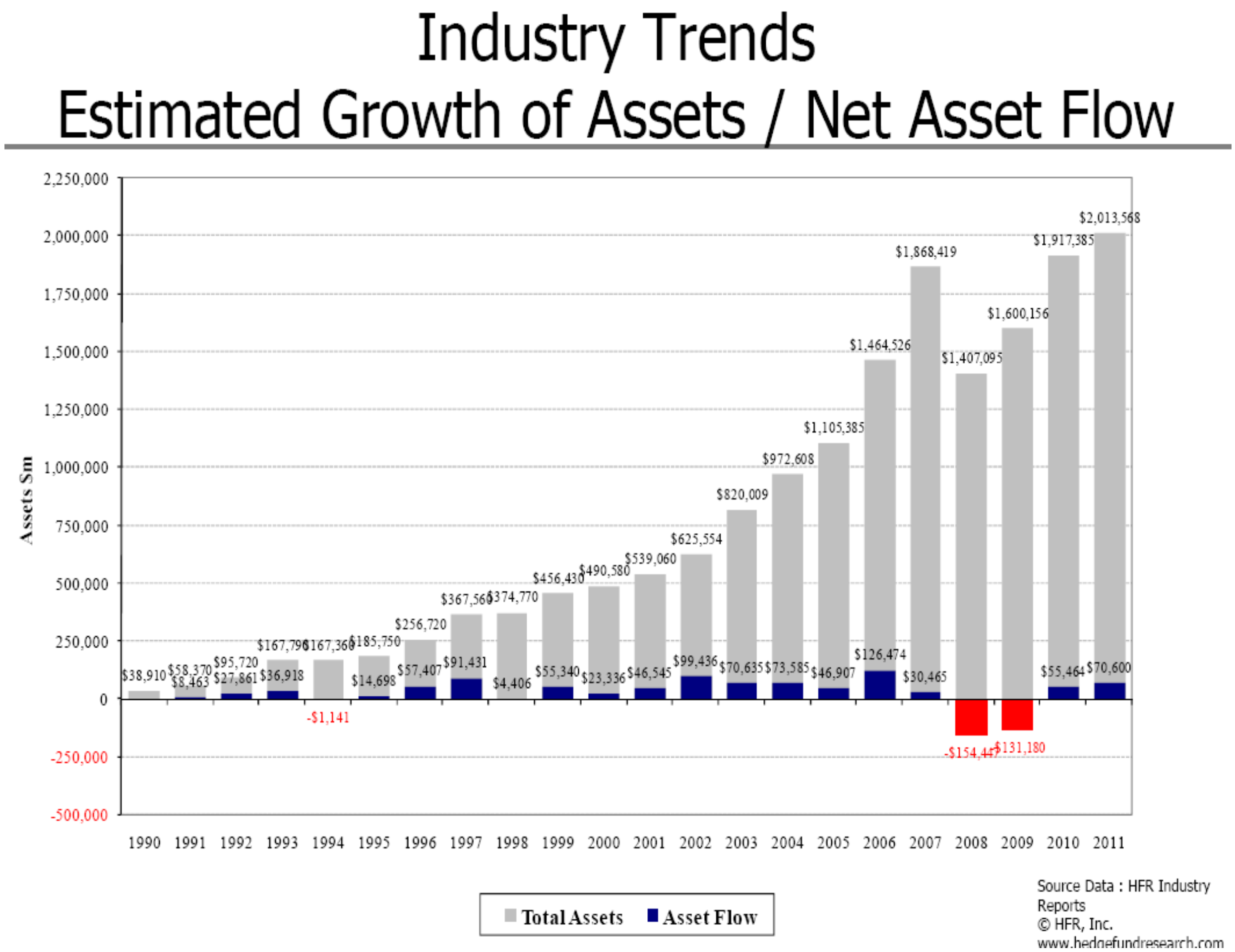
7 Appendices

7.1 *Appendix 1*



Source: HFR Industry Reports © HFR, Inc.

7.2 *Appendix 2*



Source: HFR industry reports, 2011

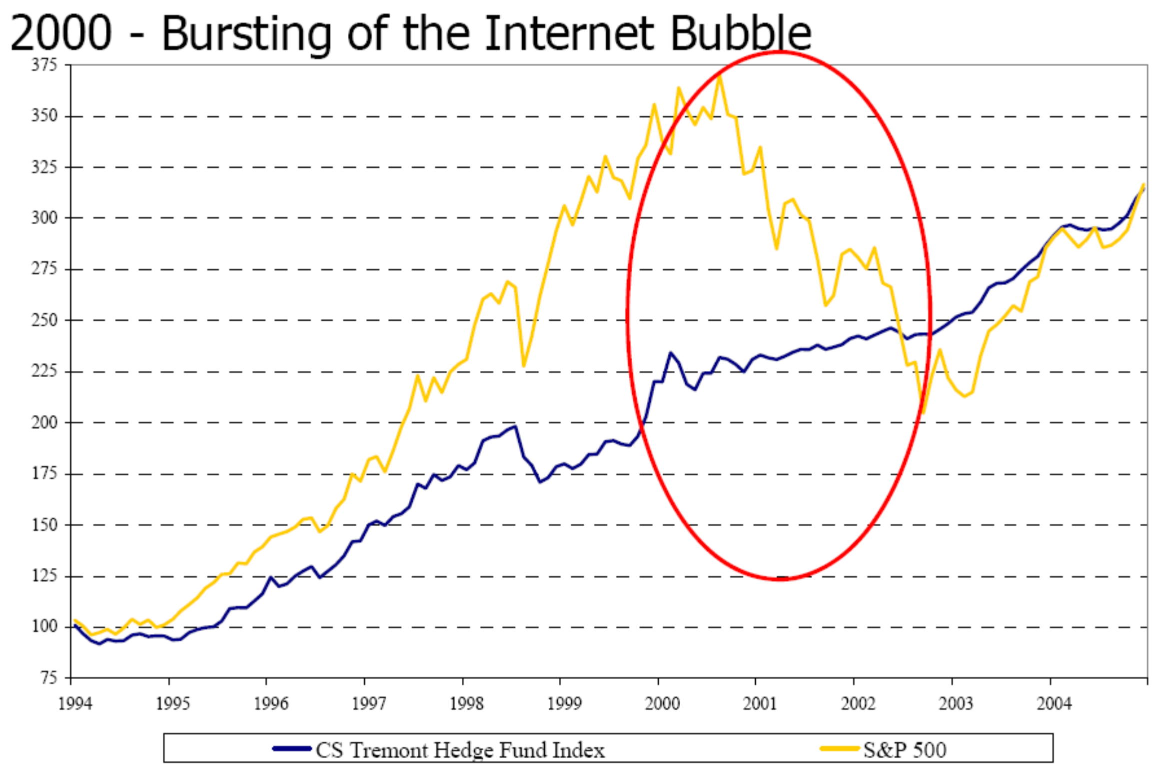
7.3 *Appendix 3*

Factors which have been indentified to drive hedge fund returns.

Asset classes	Equity Factors					Bond Factors		Other Factors	
Investment Styles	**VIX**	**Value Vs Growth**	**Small Cap Vs Large Cap**	**S&P 500 Return**	**Credit Spread**	**Bond Return**	**T-Bill 3 months**	**US Dollar**	**Commodity Index**
Equity Market Neutral			+	+	+	++	++		
Fixed Income Arbitrage	+							-	
Convertible Arbitrage			++	+	+	++	++		
Merger Arbitrage	+		++	++	-		++		
Distressed/Restructuring	+		+++						
Long/Short Equity	+	-		+++	--			-	+
Global Macro	+		++	++	-	+++		+	-
Emerging Markets	+		++	+++					

Source: Edhec European Alternatives Diversification Practices Survey 2005

7.4 *Appendix 4*



Source: The Hedge fund Index- Credit Suisse/Dow Jones

7.5 Appendix 5

Commands List in Stata Do-File

```
regress globalhedgefundindex msci jpmorganbondindex spcommodityindex

regress globalhedgefundindex msci jpmorganbondindex spcommodityindex volatilityindex
spequalweighting mscismallcap

regress macrocta msci jpmorganbondindex spcommodityindex volatilityindex spequalweighting
mscismallcap

regress equityhedge spequalweighting mscismallcap msci volatilityindex jpmorganbondindex
spcommodityindex

regress equitymarketneutral spequalweighting mscismallcap msci volatilityindex
jpmorganbondindex spcommodityindex

regress emergingmarkets msci jpmorganbondindex spcommodityindex volatilityindex
spequalweighting mscismallcap

regress distressedrestructuring msci jpmorganbondindex spcommodityindex volatilityindex
spequalweighting mscismallcap

regress eventdriven msci jpmorganbondindex volatilityindex spcommodityindex spequalweighting
mscismallcap

regress multistrategy spequalweighting mscismallcap msci jpmorganbondindex spcommodityindex
volatilityindex

regress mergerarbitrage spequalweighting mscismallcap msci jpmorganbondindex volatilityindex
spcommodityindex

regress fixedincomecorporate msci jpmorganbondindex volatilityindex spcommodityindex
mscismallcap spequalweighting
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7.6 *Appendix6*

Display of Paired T-Tests Results.

t-stat(p-value)	Global Hedge Fund Index	Fund of Funds Composite	Equity Hedge Index	Macro/CTA Index	Fixed Income-Convertible	Event Driven Index	Equity Market Neutral
Global Hedge Fund Index	-						
Fund of Funds Composite	0.939(0.349)	-					
Equity Hedge Index,	0.487(0.626)	1.208(0.228)	-				
Macro/CTA Index	0.234(0.814)	0.666(0.506)	0.057(0.954)	-			
Fixed Income-Convertible	1.582(0.115)	1.152(0.250)	1.700(0.090)	1.237(0.217)	-		
Event Driven Index	0.434(0.664)	0.483(0.629)	0.789(0.431)	0.389(0.697)	1.3409(0.181)	-	
Equity Market Neutral	0.873(0.383)	0.231(0.817)	0.967(0.334)	0.803(0.422)	0.9187(0.359)	0.4980(0.619)	-
Distressed/Restructuring	1.631(0.104)	**3.181(0.001)**	1.121(0.263)	0.744(0.457)	**2.389(0.018)**	**2.627 (0.009)**	**2.239(0.02)**
Merger Arbitrage Index	0.123(0.902)	0.551(0.582)	0.378(0.705)	0.263(0.792)	1.229(0.220)	0.236(0.813)	1.095(0.27)
Relative Value Arbitrage	0.626(0.532)	0.046(0.963)	0.801(0.424)	0.487(0.62)	1.566(0.119)	0.279(0.780)	0.220(0.82)
Fixed Income-Corporate Index	0.273(0.785)	0.487(0.626)	0.523(0.601)	0.309(0.757)	1.531(0.127)	0.110(0.912)	0.6059(0.545)
Multi-Strategy Index	0.164(0.869)	0.764(0.445)	0.434(0.664)	0.264(0.791)	1.581(0.115)	0.274(0.783)	0.8868(0.376)
Emerging Markets Global Index	0.047(0.962)	0.484(0.628)	0.155(0.876)	0.073(0.941)	1.224(0.222)	0.270(0.7870)	0.4316(0.666)
Yield Alternatives Investments	0.4746(0.635)	1.13(0.25)	0.155(0.876)	0.168(0.866)	1.728(0.085)	0.8379(0.4032)	1.204(0.230)
MSCI World Total Index	1.115(0.266)	0.882(0.378)	1.225(0.222)	1.070(0.285)	0.041(0.967)	1.0161(0.311)	0.821(0.412)
S&P GSCI	0.595(0.552)	0.766(0.444)	0.507(0.612)	0.503(0.615)	1.250(0.212)	0.679(0.497)	0.812(0.417)
JP Morgan Global Bond Index	0.202(0.840)	0.606(0.545)	0.000(1.000)	0.045(0.964)	1.216(0.225)	0.404(0.686)	0.986(0.325)

t-stat(p-value)	Distressed/Restructuring	Merger Arbitrage Index	Relative Value Arbitrage	Fixed Income-Corporate Index	Multi-Strategy Index	Emerging Markets Global Index	Yield Alternatives Investments
Distressed/Restructuring	-						
Merger Arbitrage Index	1.552(0.122)	-					
Relative Value Arbitrage	**2.55(0.011)**	0.392(0.695)	-				
Fixed Income-Corporate Inde	**2.92(0.003)**	0.131(0.895)	0.467(0.641)	-			

x							
Multi-Strategy Index	**2.24(0.026)**	0.000(1.000)	0.650(0.516)	0.235(0.813)	-		
Emerging Markets Global Index	0.903(0.367)	0.101(0.919)	0.371(0.711)	0.1985(0.842)	0.116(0.907)	-	
Yield Alternatives Investments	0.921(0.358)	0.569(0.569)	1.028(0.305)	0.807(0.420)	0.695(0.487)	0.253(0.800)	-
MSCI World Total Index	1.648(0.101)	1.088(0.277)	0.882(0.378)	1.037(0.30)	1.092(0.276)	0.941(0.348)	1.266(0.206)
S&P GSCI	0.217(0.827)	0.623(0.533)	0.754(0.451)	0.662(0.508)	0.646(0.518)	0.548(0.584)	0.4535(0.65)
JP Morgan Global Bond Index	0.706(0.480)	0.371(0.710)	0.547(0.584)	0.387(0.699)	0.327(0.743)	0.095(0.924)	0.126(0.899)

7.7 *Appendix 7*

<u>Display of Pairwise Correlation Coefficients</u>

Pairwise Correlations	S&P Equal Weight	MSCI Small Cap	MSCI	JP Morgan Bond Index	S&P Commodity Index	Volatility Index	Global Hedge F Index
Global Hedge Fund Index	0.53	0.67	0.61	-0.07	0.10	-0.38	1.00
Fund of Funds Composite	0.54	0.75	0.67	-0.12	0.14	-0.44	0.83
Equity Hedge Index,	0.63	0.73	0.70	-0.16	0.13	-0.51	0.88
Macro/CTA Index	0.08	0.24	0.14	0.01	-0.15	-0.08	0.66
Fixed Income-Convertible	0.43	0.4	0.43	-0.07	0.31	-0.28	0.62
Event Driven Index	0.66	0.78	0.72	-0.10	0.17	-0.53	0.75
Equity Market Neutral	0.25	0.37	0.30	0.02	0.04	-0.24	0.53
Distressed/Restructuring	0.61	0.74	0.65	-0.14	0.17	-0.44	0.69
Merger Arbitrage Index	0.45	0.50	0.46	-0.15	0.02	-0.43	0.43
Relative Value Arbitrage	0.49	0.56	0.53	-0.09	0.27	-0.31	0.70
Fixed Income-Corporate Index	0.62	0.70	0.64	-0.13	0.24	-0.43	0.62
Multi-Strategy Index	0.56	0.68	0.60	-0.06	0.26	-0.41	0.74
Emerging Markets Global Index	0.61	0.74	0.70	-0.17	0.07	-0.49	0.63
Yield Alternatives Investments	0.62	0.64	0.57	-0.13	0.20	-0.49	0.54

	Fund of Funds	Equity Hedge Index	Macro/ CTA Index	Fixed Income-Convertible	Event Driven Index	Equity Market Neutral	Distressed/Restructuring
Fund of Funds Composite	1.00						
Equity Hedge Index,	0.84	1.00					
Macro/CTA Index	0.46	0.45	1.00				
Fixed Income-Convertible	0.54	0.54	0.12	1.00			
Event Driven Index	0.85	0.79	0.28	0.56	1.00		
Equity Market Neutral	0.53	0.56	0.32	0.25	0.46	1.00	
Distressed/Restructuring	0.83	0.70	0.18	0.62	0.83	0.43	1.00
Merger Arbitrage Index	0.49	0.54	0.17	0.25	0.65	0.40	0.438
Relative Value Arbitrage	0.71	0.63	0.14	0.83	0.73	0.38	0.79
Fixed Income-Corporate Index	0.72	0.61	0.10	0.71	0.76	0.33	0.87

Multi-Strategy Index	0.78	0.67	0.25	0.77	0.75	0.37	0.80
Emerging Markets Global Index	0.86	0.70	0.29	0.44	0.79	0.33	0.78
Yield Alternatives Investments	0.61	0.55	0.13	0.49	0.63	0.43	0.67
	Merger Arbitrage Index	**Relative Value Arbitrage**	**Fixed Income-Corporate Index**	**Multi-Strategy Index**	**Emerging Markets Global Index**	**Yield Alternatives Investments**	
Merger Arbitrage Index	1.000						
Relative Value Arbitrage	0.37	1.00					
Fixed Income-Corporate Index	0.40	0.83	1.00				
Multi-Strategy Index	0.39	0.86	0.8681	1.00			
Emerging Markets Global Index	0.42	0.60	0.72	0.69	1.00		
Yield Alternatives Investments	0.37	0.62	0.65	0.64	0.59	1.00	

7.8 *Appendix 8*

Detailed Multi-Factor Model Results

Global Hedge Fund Index	**Main Model 1**	**T-Stats**	**Main Model 2**	**T-Stats**
Variables	Coef. (std. err.)	T (p>t)	Coef. (std. err.)	T (p>t)
MSCI	0.26 (0.02)	9.83 (0.00)	0.202 (0.069)	2.90 (0.004)
JP Morgan Bond	0.023 (0.07)	0.34 (0.73)	0.007 (0.063)	0.12 (0.905)
Commodities	0.001 (0.017)	0.08 (0.93)	0.013 (0.016)	0.84 (0.403)
Volatility Index			0.016 (0.008)	1.92 (0.056)
S&P Equal W.			-0.16 (0.054)	-2.94 (0.004)
MSCI Small Cap			0.25 (0.042)	6.02 (0.00)
alpha	0.004 (0.001)	3.34 0.001	0.003 (0.001)	3.14 (0.002)
Diagnostic Tests:	No of obs.: 172		No of obs.: 172	
F- Test	34.20 (0.00)		27.40 (0.00)	
Adjusted-R-square	0.3681		0.4809	
R-Square	0.3792		0.4991	

Sub Strategies	**Macro/CTA**	**T-Stats**	**Equity Hedge**	**T-Stats**
Variables	Coef. (std. err.)	T (p>t)	Coef. (std. err.)	T (p>t)
MSCI	0.12 (0.118)	1.01 (0.31)	0.24 (0.083)	2.98 (0.003)
JP Morgan Bond	0.101 (0.10)	0.94 (0.34)	-0.10 (0.075)	-1.39 (0.166)
Commodities	-0.06 (0.027)	-2.26 (0.02)	.024 (0.019)	1.30 (0.195)
Volatility Index	0.01 (0.014)	0.71 (0.48)	.001 (0.010)	0.17 (0.862)
S&P Equal W.	-0.25 (0.092)	-2.77 (0.006)	-.148 (0.064)	-2.28 (0.024)
MSCI Small Cap	0.27 (0.072)	3.74 (0.000)	.27 (0.050)	5.30 (0.000)
alpha	0.005 (0.002)	2.49 (0.01)	.004 (0.001)	2.86 (0.005)
Diagnostic Tests:	No of obs.: 172		No of obs.: 172	
F- Test	4.93 (0.0001)		36.72 (0.00)	
Adjusted-R-square	0.1212		0.5562	
R-Square	0.1520		0.5718	

Sub Strategies	**Equity Market Neutral**	**T-Stats**	**Emerging Markets**	**T-Stats**
Variables	Coef. (std. err.)	T (p>t)	Coef. (std. err.)	T (p>t)
MSCI	0.032 (0.044)	0.73 (0.465)	0.494 0.129	3.82 (0.00)
JP Morgan Bond	0.037 (0.039)	0.93 (0.354)	-0.164 0.117	-1.40 (0.164)
Commodities	0.0005 (0.010	0.06 (0.953)	0.006 (0.03)	0.22 (0.828)
Volatility Index	-0.001 (0.005)	-0.21 (0.832)	0.011 (0.015)	0.72 (0.475)
S&P Equal W.	-0.068 (0.034)	-1.99 (0.048)	-0.36 (0.101)	-3.58 (0.00)
MSCI Small Cap	0.09 (0.026)	3.62 (0.00)	0.502 (0.078)	6.37 (0.00)
alpha	0.003 (0.0007)	3.99 (0.00)	0.004 (0.002)	2.04 (0.043)
Diagnostic Tests:	No of obs.: 172		No of obs.: 172	
F- Test	5.75 (0.0001)		42.01 (0.00)	
Adjusted-R-square	0.1428		0.5900	
R-Square	0.1729		0.6044	

Sub Strategies	**Distressed /Restructuring**	**T-Stats**	**Event Driven**	**T-Stats**
Variables	Coef. (std. err.)	T (p>t)	Coef. (std. err.)	T (p>t)
MSCI	0.072 (0.065)	1.10 (0.273)	0.158 (0.059)	2.65 (0.01)
JP Morgan Bond	-0.082 (0.059)	-1.38 (0.170	-0.015 (0.054)	-0.29 (0.77)
Commodities	0.036 (0.015)	2.42 (0.017)	0.027 (0.013)	2.02 (0.04)
Volatility Index	0.011 (0.008)	1.44 (0.152)	0.002 (0.007)	0.39 (0.69)
S&P Equal W.	-0.090 (0.051)	-1.75 (0.082)	-0.115 (0.046)	-2.47 (0.01)
MSCI Small Cap	0.303 (0.040)	7.55 (0.000)	0.262 (0.036	7.20 (0.00)
alpha	0.005 (0.001)	4.59 (0.000)	0.002 (0.001)	2.85 (0.005)
Diagnostic Tests:	No of obs.: 172		No of obs.: 172	
F- Test	37.67 (0.0001)		50.52 (0.000)	
Adjusted-R-square	0.5627		0.6347	
R-Square	0.5780		0.6475	

Sub Strategies	**Multi Strategy**	**T-Stats**	**Merger Arbitrage**	**T-Stats**
Variables	Coef. (std. err.)	T (p>t)	Coef. (std. err.)	T (p>t)
MSCI	0.060 (0.049)	1.20 (0.231)	-0.008 (0.046)	-0.18 (0.855)
JP Morgan Bond	-0.018 (0.045)	-0.40 (0.689)	-0.053 (0.042)	-1.27 (0.208)
Commodities	0.044 (0.011)	3.84 (0.000)	-0.003 (0.0106)	-0.37 (0.713)
Volatility Index	0.009 (0.006)	1.54 (0.126)	-0.011 (0.005)	-2.05 (0.042)
S&P Equal W.	-0.059 (0.038)	-1.53 (0.127)	0.002 (0.036)	0.06 (0.951)
MSCI Small Cap	0.192 (0.030)	6.30 (0.000)	0.074 (0.028)	2.63 (0.009)
alpha	0.005 (0.001)	3.77 (0.000)	0.004 (0.0007)	5.68 (0.000)
Diagnostic Tests:	No of obs.: 172		No of obs.: 172	
F- Test	29.53 (0.0001)		10.84 (0.000)	
Adjusted-R-square	0.5002		0.2567	
R-Square	0.5178		0.2828	

Sub Strategies	**Fixed Income**	**T-Stats**
Variables	Coef. (std. err.)	T (p>t)
MSCI	0.070 (0.062)	1.13 0.26
JP Morgan Bond	-0.077 (0.057)	-1.35 0.178
Commodities	0.050 (0.014)	3.47 0.001
Volatility Index	0.011 (0.007)	1.56 0.121
S&P Equal W.	-0.032 (0.048)	-0.67 0.504
MSCI Small Cap	0.074 (0.028)	0.78 0.000
alpha	0.0027 (0.001)	2.59 0.011
Diagnostic Tests:	No of obs.: 172	
F- Test	32.33 (0.00)	
Adjusted-R-square	0.5236	
R-Square	0.5404	